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The development of mathematics expectancy-value profiles during the secondary–tertiary transition into STEM fields

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Abstract

Background To master the secondary–tertiary transition into fields of science, technology, engineering, and mathematics (STEM), academic self-beliefs play a pivotal role, especially those related to learning mathematics. The framework of expectancy-value theory has been used widely in primary and secondary education and partly in tertiary education to assess the self-beliefs of students in terms of expectancy of success and perceived value of mathematics. Based on this framework, we measured how the intrinsic value, the attainment value, the utility value, and the cost of learning mathematics as well as the expectancy of success when learning mathematics developed during the secondary–tertiary transition of students into STEM fields. Data were collected in a quantitative repeated-measures questionnaire study with two measurement points (measurement point 1: $n=710$, measurement point 2: $n=487$, listwise: $n=409$). We conducted a latent profile analysis to identify the prevalent patterns of mathematics self-beliefs, called *profiles*, at each of the two measurement points. We studied the relation of these profiles to prior education, achievement at school, and achievement at university. By performing a latent transition analysis, we determined the probabilities of transitioning from the initial profiles to the posterior profiles.

Results Our analysis revealed four distinct prevalent profiles at each measurement point, ranging from highly favorable (i.e., high expectancy, high value, low cost) to highly unfavorable with respect to learning mathematics. The profiles with favorable manifestations remained stable over time, while those with undesirable manifestations deteriorated further. We observed a sharp increase in cost across all profiles. Prior achievement correlated strongly with profile membership.

Conclusions The expenditure of time and energy increased sharply during the secondary–tertiary transition, independently of the students' initial motivational patterns. The perceived utility of mathematics for potential future careers was shown to be a significant source of motivation. The role of mathematics in future careers should thus be made visible in university teaching. Keeping the detrimental development of initially undesirable motivational profiles in mind, university teachers should create ample opportunities for students to gain a sense of accomplishment.

Keywords Academic achievement, Expectancy-value theory, Latent profile analysis, Latent transition analysis, Mathematics, Secondary–tertiary transition, Self-beliefs

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Introduction

The availability of a workforce trained in the fields of science, technology, engineering, and mathematics (STEM) is a key prerequisite for economic growth and competitiveness. Beyond this, STEM education has been linked to promoting societal well-being and equity (Ng, 2019; Walker, 2015). International organizations have identified a worrisome decline in STEM participation and call for measures to counteract this trend (see, e.g., Marginson et al., 2013). Governments are therefore well advised to encourage youths to pursue STEM careers. Heublein et al. (2017) have shown that an alarmingly high proportion of young adults who enter tertiary education in a STEM field do not follow through, identifying problems in performance and lack of study motivation as the main reasons. In particular, the rate of dropout from STEM field degree courses has been reported to be at a very high level in Germany (50% between 2016 and 2020; Heublein et al., 2022) and Austria (56% between 2010 and 2020; Statistics Austria, 2022). It is therefore important to identify beginning STEM field students who have the potential to succeed but are at risk of quitting and to support them.

It has been observed that students on career paths in STEM fields are at a particularly high risk for dropout soon after transitioning from secondary school to higher education (Heublein et al., 2017). This becomes apparent in their mathematics self-concept. For example, Di Martino et al. (2023) showed that, while the mathematics self-concept of students entering mathematics degree courses is typically high initially, they soon tend to adopt less favorable self-beliefs. Notwithstanding individual differences, the school mathematics self-concept of students has been found to remain stable at the transition, while both their general self-concept and university mathematics self-concept tend to decrease (Rach et al., 2021). The decline in mathematics self-concept has repeatedly been attributed to the big-fish-little-pond effect (Marsh, 1987) in empirical works (e.g., Loyalka et al., 2018; von Keyserlingk et al., 2020). This effect is caused by changes in the peer group: High-achieving students in school perceive themselves as superior because their abilities surpass the average level of their peers. Consequently, they develop a high academic self-concept. However, when these students transition to university, their reference group changes. University students typically exhibit higher average levels of ability than their school peers, which results in a decrease in their self-concept.

In non-STEM fields, an increase in favorable autonomous motivation has been observed in the course of higher education (e.g., Kyndt et al., 2015; Ratelle et al., 2004). At the same time, less favorable controlled motivation has been found to remain stable (e.g., Kyndt et al., 2015) or even to decrease (e.g., Ratelle et al., 2004). Kyndt et al. (2015) found unfavorable amotivation to decrease at the secondary–tertiary transition and to remain stable thereafter.

Comparing these results with the high dropout rates in higher education suggests that the findings of Kyndt et al. (2015) and Ratelle et al. (2004) might be specific to students who have already overcome potential challenges and remain in their respective degree programs. This potential positive selection bias as well as the lack of STEM focus in prior studies call for a closer look at the development of motivational aspects of subgroups of students. Expectancy-value theory is a framework for measuring aspects such as achievement-related choices and persistence. It is a particularly suitable framework to study the secondary–tertiary transition, where many achievement-related choices are made and where persistence is crucial for success. Research based on expectancy-value theory using person-centered approaches has been conducted in primary, secondary, and tertiary education (e.g., Lazarides et al., 2022; Perez et al., 2023; Schweder & Raufelder, 2022).

In this study, we adopt a person-centered repeated-measures approach to identify prevalent patterns of self-beliefs related to learning mathematics during the secondary–tertiary transition of students into STEM fields and capture their development, all through the lens of expectancy-value theory.

Expectancy-value theory

Expectancy-value theory (Atkinson, 1958; Eccles, 1983; Eccles & Wigfield, 2020) is a framework that has been used widely to measure self-beliefs of students, and thus to predict achievement motivation, performance, persistence, and achievement-related choices. Expectancy beliefs refer to the subjective assessment of the chance of success or failure when participating in achievement-oriented tasks (Spence & Helmreich, 1983). Expectancy of success is a domain-specific determinant of behavioral choice with respect to education and career (Eccles, 1983). Students with high expectancy of success, as measured by their level of self-efficacy, also exhibit high engagement and persistence (Scherrer & Preckel, 2019). The value component may be described as "the degree of anticipated satisfaction or pride in succeeding at a task or the degree of anticipated shame in failing" (Spence & Helmreich, 1983, p. 33). Four value beliefs can be differentiated: intrinsic value (sense of joy when performing a task), attainment value (personal importance of doing well at a task and personal relevance of a task or a domain), utility value (perceived usefulness of engaging in a task or a domain), and cost (undesirable consequences of engaging in a task). Intrinsic value and attainment value are closely tied to intrinsic motivation, while utility value is related to extrinsic motivation (Trautwein et al., 2013). Intrinsic motivation, in turn, has been shown to be closely related to academic achievement (Scherrer & Preckel, 2019).

The role of expectancy-value theory in STEM education

The claim that expectancy of success and value beliefs are "the most proximal psychological determinants of task and activity choice, performance, and engagement in the chosen activities" (Eccles, 1983) is the bedrock of expectancy-value theory. In the context of learning mathematics, Trautwein et al. (2012) confirmed the potential of the expectancy-value model to predict achievement in mathematics among students in grade 13 of German high schools. In their study, they found expectancy-value beliefs related to learning mathematics to correlate strongly with school type and little with gender or prior achievement. Harackiewicz et al. (2012) showed that a utility-value-based intervention led to increased persistence of students in taking STEM university courses. Thus, high expectancy of success and value beliefs are desirable for learning mathematics in the sense that they are positively related to both performance and persistence, which play an important role for a successful secondary–tertiary transition into STEM fields. In addition, expectancy-value aspects were found to predict the development of computational thinking skills (Jiang et al., 2024).

Person-centered approaches applying expectancy-value theory

Numerous works have applied expectancy-value theory in person-centered approaches to investigate the extent to which expectancy-value profiles predict achievement in the context of primary and secondary education as well as the evolution of such profiles and the transitions between them over time. Schweder and Raufelder (2022) observed across various subjects that self-directed learning sequences led students in grades 6 to 9 to transition to more desirable expectancy-value profiles. By contrast, in their study without a specific intervention, Lazarides et al. (2022) found that expectancy-value profiles of mathematics learners from grade 9 to 10 were mostly stable.

Fong et al. (2021) studied the development of 23,000 students from grade 11 of high school until three years after graduation in the United States. Five distinct expectancy-value profiles were identified: low math/low science; high math/low science; low math/high science; moderate math/moderate science; high math/high science. As one would expect, the high math/high science profile had the highest math grade point average (GPA), science GPA, and academic persistence rate, while the students with low math/low science profile showed the lowest academic results within the cohort. Students in the low math/high science profile and in the moderate math/moderate science profile showed statistically significantly lower persistence in tertiary education than their peers with high math/high science profile.

Studies which combine expectancy-value theory with person-centered approaches in the context of tertiary education are scarce. A notable exception is the study of Perez et al., (2019b) who investigated expectancy-value profiles of students in STEM fields upon their arrival at a highly selective private university in the United States. GPA and course completion rate in STEM majors were recorded at the end of the first and at the end of the fourth year at university. The first-semester profile with high expectancy and value beliefs and low effort cost had significantly higher GPA and course completion rates than the profile with moderate expectancy, value, and cost beliefs. The authors did, however, not investigate how the profiles of individual students evolved in the course of their respective degrees. In a more recent study, Perez et al. (2023) identified four distinct expectancy-value profiles of first-year and second-year chemistry students. The by far most prevalent profile of students with high confidence and low to moderate costs showed the best outcomes in the final exam of a chemistry course.

Summary of the state of research

The essence of available studies which apply expectancy-value theory using person-centered approaches is that more desirable profiles exhibit better academic achievement and persistence. Longitudinal studies showed that profiles remain mostly stable under stable conditions, but transitions between profiles of different shape appear more frequently after interventions. Two studies created profiles only at a single point of time and observed the development of outcome variables but did not investigate whether the profiles changed over time. While all these studies applied expectancy-value theory either in the context of primary or secondary education or in very specific contexts of tertiary education, there is a lack of studies that investigate the development of expectancy-value profiles at the secondary–tertiary transition, in particular of students in STEM fields. As for tertiary education, the relationship between individual expectancy-value aspects and school type or prior achievement has been examined, but the relations of these variables with expectancy-value profiles are still to be investigated.

Our study aims to add the perspective from the secondary–tertiary transition by attempting to answer the following research question: How do the motivational patterns of beginning STEM field students develop during their first semester at university?

The present study

The goal of this work is to identify the prevalent expectancy-value profiles among beginning STEM field students first upon arrival at university (*initial profiles*) and then after the first two months at university (*posterior profiles*). We study the transitions of students between these profiles during the initial phase of their degrees and how these profiles relate to prior education and achievement.

Specifically, we operationalize the general research question stated above by the following concrete research questions (RQs) and corresponding hypotheses:

(RQ1) What are the initial and posterior expectancy-value profiles of STEM field students?

Previous findings (Jiang & Zhang, 2023; Perez et al., 2019b) have led us to hypothesize that we would find initial profiles with high intrinsic and extrinsic value beliefs, high expectancy beliefs, and low cost (H1a) as well as complementary profiles (H1b). Regarding posterior profiles, we hypothesize that the prevalent profiles would show high extrinsic value beliefs, low expectancy beliefs, and high cost (H1c), while profiles with high intrinsic value beliefs, high expectancy beliefs and low cost (H1d) would also be found.

(RQ2) How are the initial profiles related to prior academic achievement and school type?

In view of the high mathematics self-concept which is typically held by beginning STEM field students (Di Martino et al., 2023) as well as previously observed positive correlations between prior achievement and expectancy-value beliefs (Trautwein et al., 2012), we hypothesize that higher prior academic achievement is characteristic of profiles with high expectancy and value beliefs and low cost (H2a). Since the educational pathways in Austria which lead to university admission vary considerably, we hypothesize that there are initial differences in the expectancy-value beliefs of students who graduated from academic secondary schools and those of students who graduated from Higher Federal Technical Colleges. Academic secondary schools follow a broad educational model with a focus on preparation for university education, which leads us to hypothesize that they initially hold more adaptive expectancy-value beliefs than their fellows graduating from Higher Federal Technical Colleges (H2b).

(RQ3) How are the posterior profiles related to academic achievement and school type?

We hypothesize that the posterior profiles of students who graduated from schools of different type would not differ significantly (H3a). By contrast, we hypothesize that profiles with higher expectancy and value beliefs would tend to show higher achievement at university than other profiles (H3b).

Methods

This work is based on a repeated-measures questionnaire study with two waves that comprises scales on expectancy-value constructs, conceptions of mathematics, and learning strategies. The specific focus of this paper is to identify prevalent patterns of expectancy-value aspects among students at the secondary–tertiary transition into STEM fields. These patterns of observable variables (i.e., the expectancy-value aspects; see section "Measures"), subsequently referred to as *profiles*, are modeled as a latent variable. Since we hypothesize that there are several different distinct patterns of observable variables, even though these patterns are not observable directly, we adapt a latent model approach. As a result, each student is assigned to the profile that best fits their individual motivational pattern. Finally, we examine to which extent students remain in their original profile or transition to a different profile using latent transition analysis.

Study design

The data collection at measurement point 1 (MP1) took place in the first session of the preparatory course for incoming students offered by TU Wien, Austria, in September 2022. Though voluntary, participation in this course was strongly recommended by the university. The course focused on the topics functions, vector algebra, complex numbers as well as differential and integral calculus. While the core aspects of the course were the same for all participants, students enrolled in a computer science degree course went through a slightly different course program than the other students. Students received credits for the successful completion of the course. We chose to collect data during this course over approaching students electronically or in an asynchronous setting. Indeed, this would likely have resulted in a selection bias, with participation chiefly by the most diligent students. The students were shown a video at the beginning of the preparatory course in which the authors invited them to participate in the study and explained the procedure and the aim of the study. To increase the readiness of students to participate in the study, vouchers for the university's bookstore were raffled among the participants. Participation in this study was voluntary and subject to informed consent of the students. The questionnaire was provided in German language.

The questionnaire was administered to the students for a second time (MP2) roughly two months into the winter

Table 1 Constructs on expectancy and value beliefs included in the questionnaire, corresponding reliabilities (McDonald's ω), and descriptive statistics

Construct	Items	Sample item	ω		M (SD)	
			MP1	MP2	MP1	MP2
Expectancy						
Self-efficacy	3	I am convinced that I can understand even the most difficult mathematical material presented in the lectures.	0.86	0.89	4.14 (1.01)	3.58 (1.29)
Value beliefs						
Intrinsic value	3	I like doing math.	0.92	0.93	4.37 (1.04)	3.88 (1.24)
Attainment value						
Importance of achievement	3	It is important to me to be good at math.	0.87	0.90	4.52 (0.99)	3.93 (1.24)
Personal importance	3	Math is very important to me personally.	0.85	0.89	4.14 (1.02)	3.79 (1.19)
Utility value						
General utility value	2	Math is very useful to me.	0.66[a]	0.71[a]	4.44 (0.95)	3.84 (1.16)
Utility for job	3	Being good at math will pay off for my professional future.	0.90	0.95	5.11 (0.87)	4.64 (1.21)
Cost						
Effort required	3	Learning math exhausts me.	0.85	0.87	3.22 (1.08)	4.04 (1.16)
Emotional cost	3	When I deal with math, I get annoyed.	0.73	0.79	2.26 (0.92)	2.91 (1.16)
Opportunity cost	3	I have to give up a lot to do well in math.	0.83	0.86	2.98 (1.07)	4.09 (1.15)

$n_{MP1} = 409$, $n_{MP2} = 409$; *M* mean, *SD* standard deviation, *MP* measurement point

[a] To assess the reliability of the two-item scale, the Spearman–Brown coefficient was used instead of McDonald's ω

term via email. During this period, students did not sit major exams, which may serve as a trigger for dropout. We chose to limit the period between the measurement points to two months to avoid drawing a highly positively selected sample while still capturing the transition period. To enhance the response rate, large cohorts of the sample were given time to fill in the questionnaire in lectures of their respective degree courses.

Participants

710 students participated in the survey at MP1, and 487 students participated at MP2. The responses of the 409 students (age: range = 17–57 years, $M = 19.9$ years, SD = 3.0 years) who completed the questionnaire at both measurement points were the basis for data analysis. In the resulting sample, 292 participants identified as male (71.4%), 111 as female (27.1%), 2 as diverse (0.5%), and 4 participants provided no answer to the question on gender (1.0%). 87.8% completed their schooling in Austria and 95.6% in the period between 2019 and 2022. The prevalent Austrian school types[1] attended by these participants were academic secondary schools (51.0% of the students graduating in Austria) which focus on general education and usually comprise four years at the upper secondary level or Higher Federal Technical Colleges (41.8%) which offer specialized education in STEM fields over five years. All the participants enrolled in a degree program in STEM fields (e.g., Civil Engineering, Computer Science, Electrical Engineering, Technical Chemistry, Technical Mathematics, Technical Physics). 88.7% started a degree program at university for the first time. Three out of four students (75.0%) had family members with university experience. Almost all the participants (97.1%) studied full-time.

Measures

To survey students' various value beliefs and expectancy of success in learning mathematics, we used scales from the validated German questionnaire of Gaspard et al. (2021) (see Table 1). Specifically, utility value was measured by the subscales *general utility value* and *utility for job*, attainment value was measured by the subscales *importance of achievement* and *personal importance*,

[1] For an overview of the school types in Austria see https://www.bildungssystem.at/en/.

intrinsic value was measured by the subscale *intrinsic value*, and cost was measured by the subscales *effort required*, *emotional cost*, and *opportunity cost*. Expectancy was measured using the subscale *self-efficacy*. For estimating the reliability, McDonald's ω was computed for each scale at each measurement point. The results show acceptable reliability ($\omega > 0.6$) for general utility value and emotional cost and excellent reliability ($\omega > 0.8$) for all the other scales.

Items which had originally been designed for the context of studying mathematics in schools were adapted to the university context. Each item was surveyed using a six-point Likert scale with 1 representing the lowest level of agreement ("do not agree at all") and 6 the highest level of agreement ("totally agree"). In the questionnaire, the respondents were repeatedly reminded that they should focus their personal attitudes towards mathematics when answering the questions.

As control variables, we inquired the students' grade in the national school leaving examination and asked the participants for their consent to use their scores in the exam which they would take after concluding the preparatory course in our research. This final exam consisted of problems with slightly randomized data so the students would not be working on identical problems. Those students who were enrolled in a computer science degree program ($n = 30$) worked on a comparable but slightly different version of the exam than those enrolled in other degree programs ($n = 166$). The scores were recoded to percentages with 100% reflecting the maximum score of 20. The questionnaire also included questions on sociodemographic variables that we report in the subsection "Participants".

Data preparation

The dataset was prepared for analysis using *SPSS 29* and *R 4.3.3*. Data preparation included the deletion of data records with no ID, records of students who were not first-semester students, and students who participated multiple times at the same measurement point based on the ID they provided. Moreover, we identified careless responses based on short duration of survey completion and low standard deviation in the coded responses (i.e., same response to all items) and deleted them. Following this procedure, we arrived at data from 788 students which we used for the data analysis. The individual datasets from the two measurement points were joined based on the students' ID which they provided.

Analysis

To identify the prevalent expectancy-value profiles at each of the two measurement points and the transition of individual students from profiles at MP1 to those at MP2, we opted for latent modeling. For the classification of the expectancy-value profiles, we introduced a categorical latent variable representing the profile to which each student was assigned. We used the scale means of several subscales of the questionnaire as the profile indicators of the expectancy-value profiles. Specifically, we included utility for job as an extrinsic value, personal importance and intrinsic value as intrinsic values, opportunity cost as an aspect of cost, and self-efficacy as the expectancy component.

For data analysis, we considered the responses of 710 students at MP1 and of 487 students at MP2. Of these students, 409 participated at both measurement points. Using *Mplus 8.8* and following Asparouhov and Muthén (2014a), we ran a latent profile analysis (LPA) separately at each measurement point to identify the profiles that best represent the prevalent configurations of expectancy-value variables (see Appendix A). Since this method requires to specify an assumption regarding the variance and covariance structure of the variables within and across the profiles, we constrained the variances to be equal across the profiles and fixed the covariance at 0 within the profiles (see also Masyn, 2013). After identifying the profiles, we performed a latent transition analysis (LTA) following the procedure outlined by Asparouhov and Muthén (2014a) and Morin and Litalien (2017).

Overall, we ran the LPA ten times, namely for solutions with 2, 3, 4, 5, and 6 profiles at each of the two measurement points. To decide on a profile solution (i.e., on the number of profiles) at each measurement point, we reviewed the fit indices which reflect the goodness of classification. A necessary condition for us to accept a profile solution was that at least 5% of the sample would be allocated to each of the profiles and that the average membership probability within each profile would be 80% or more; see also Weller et al. (2020). From the profile solutions meeting these conditions, we selected the solution with the best fit values. In terms of the fit values, we consulted the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the Sample-Size Adjusted BIC (SABIC); the smaller the value of these criteria, the better the fit (Weller et al., 2020). We report the strength of relationships between the profile variables at each measurement point in terms of bivariate correlations in Table 2. In the LPA, the probabilities by which a given participant at a given measurement point belonged to a given profile were determined. The better the participants' individual scores aligned with the mean values of a profile, the greater the probability of belonging to that specific profile. For additional, detailed information on the LPA, see Appendix A. After identifying the initial and posterior profiles, we ran a LTA on them. This is a probabilistic approach to examine patterns in the transitions of

Table 2 Bivariate correlations of the profile variables at the first (MP1) and the second measurement point (MP2)

	Construct	1	2	3	4	5	6	7	8	9	10	11	*n*	M	SD
1	Self-efficacy MP1	–											409	4.14	1.01
2	Self-efficacy MP2	0.496***	–										409	3.58	1.29
3	Intrinsic value MP1	0.428***	0.262***	–									409	4.37	1.04
4	Intrinsic value MP2	0.339***	0.512***	0.692***	–								406	3.88	1.24
5	Personal importance MP1	0.342***	0.248***	0.662***	0.544***	–							409	4.14	1.02
6	Personal importance MP2	0.299***	0.505***	0.534***	0.769***	0.657***	–						409	3.78	1.19
7	Utility for job MP1	0.177***	0.068	0.339***	0.214***	0.415***	0.258***	–					409	5.11	0.86
8	Utility for job MP2	0.149**	0.378***	0.288***	0.479***	0.347***	0.584***	0.435***	–				409	4.64	1.21
9	Opportunity cost MP1	− 0.345***	− 0.176***	− 0.396***	− 0.223***	− 0.105*	− 0.127**	− 0.078	− 0.068	–			409	2.98	1.07
10	Opportunity cost MP2	− 0.241***	− 0.472***	− 0.231***	− 0.364***	− 0.100*	− 0.227***	− 0.037	− 0.186***	0.457***	–		409	4.10	1.15
11	School leaving exam (grade)	− 0.181***	− 0.142**	− 0.389***	− 0.306***	− 0.187***	− 0.188***	− 0.096	− 0.114*	0.340***	0.202***	–	356	1.75	0.89
12	Course exam (relative score)	0.046	0.222**	0.049	0.160*	0.069	0.141*	0.045	− 0.009	− 0.023	− 0.131	− 0.333***	196	0.60	0.19

Absolute values of 0.1 can be interpreted as small relationships, absolute values of 0.3 as medium relationships, and absolute values of 0.5 as strong relationships

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Table 3 Confirmatory factor analysis to test the presumed four-factor model of value beliefs

	CFI	TLI	RMSEA	SRMR
Measurement point 1	0.997	0.996	0.043 [0.028, 0.058]	0.027
Measurement point 2	0.998	0.998	0.041 [0.025, 0.056]	0.025

CFI Comparative Fit Index, *TLI* Tucker–Lewis Index, *RMSEA* root mean square error of approximation (90% confidence interval), *SRMR* standardized root mean square residual

students from the initial profiles to the posterior profiles. Since the LTA uses all the profile membership probabilities, it is able to provide particularly nuanced information on the dynamics of transition between profiles.

The results of the final exam of the preparatory course were available from 47.9% of the participants; denial of consent to process exam results or students not participating in the exam led to this reduced availability of data. Equality tests of means using the BCH procedure were used to test for relationships between profile membership with the grade in the school leaving examination and with the score in the final exam of the preparatory course. The BCH procedure after Bolck et al. (2004) allowed comparisons between profiles while observing measurement errors of the profile variables using weights. For detailed information on this procedure, we refer to the explications of Asparouhov and Muthén (2014b). We used multinomial logistic regression to examine whether the school type predicts profile membership.

To evaluate the construct validity of the scales, we performed a confirmatory factor analysis of all items assumed to measure the value beliefs included in the questionnaire. We checked for sufficient distinctness of the four value beliefs intrinsic value, personal importance, utility for job, and opportunity cost. We used the common fit indices and thresholds (Hu & Bentler, 1999) to infer good model fit (CFI > 0.95, TLI > 0.95, RMSEA < 0.06, SRMR < 0.08). The results showed excellent model fit at both measurement points for the presumed four-factor structure of the value beliefs (see Table 3).

We examined potential selection effects as students who only participated at MP1 might have withdrawn from their degree program. We conducted *t*-tests to compare these students with those who participated at both measurement points.

Results

Latent profiles

Based on multiple information criteria (see Tables 4 and 5), a four-profile model was found to fit the data at both measurement points suitably by the criteria specified in the Analysis section. The subsequent analyses were based on this four-profile model.

Among the initial profiles (see Fig. 1 and Table 6), a profile with highly adaptive manifestation of all constructs, i.e., high expectancy (self-efficacy), high intrinsic value beliefs (intrinsic value, attainment value), high extrinsic value beliefs (utility value), and low cost, was found. We denote this profile as *Initial profile 1* or as the *high all except low cost profile.*

The second most adaptive profile at MP1 differed from Profile 1 in terms of a somewhat lower level of expectancy and intrinsic value beliefs. More than half of the sample holds this profile, which we denote as *Initial Profile 2* or the *high extrinsic profile.*

We also found a less adaptive prevalent profile that had intermediate values in all the five variables, which we refer to as *Initial profile 3* or as the *medium all profile.*

The profile with the most maladaptive manifestation of constructs had low self-efficacy, low intrinsic and high extrinsic value beliefs, and moderate cost. We denote this smallest profile (8.3%) as *Initial profile 4* or as the *low intrinsic, high extrinsic profile.*

Since we specified a model with profile invariant residual variances in our analysis, the variance of corresponding variables is equal in all profiles. Overall, the analysis of the initial profiles has resulted in two adaptive profiles

Table 4 Fit indices for different latent profile solutions at measurement point 1

Profiles	#Par	LL	LL Replicated	AIC	CAIC	BIC	SABIC	Entropy	VLMR	ALRT	Relative profile sizes
2	16	− 2738.9	Yes	5509.8	5590.0	5574.0	5523.3	0.696	0.004	0.005	0.55/0.45
3	22	− 2678.0	Yes	5400.0	5510.3	5488.3	5418.5	0.765	0.100	0.105	0.55/0.31/0.14
4	**28**	**− 2638.5**	**Yes**	**5332.9**	**5473.3**	**5445.3**	**5356.4**	**0.791**	**0.019**	**0.021**	**0.52/0.28/0.12/0.08**
5	34	− 2616.1	Yes	5300.3	5470.7	5436.7	5328.8	0.801	0.260	0.267	0.48/0.22/0.16/0.10/0.04
6	40	− 2597.0	Yes	5274.0	5474.5	5434.5	5307.6	0.807	0.060	0.065	0.45/0.22/0.16/0.09/0.04/0.03

The row set in bold corresponds to the model chosen for the analysis

#Par number of estimated parameters, *LL* log-likelihood, *AIC* Akaike Information Criterion, *CAIC* consistent AIC, *BIC* Bayesian Information Criterion, *SABIC* sample-size adjusted BIC, *VLMR* Vuong–Lo–Mendell–Rubin likelihood ratio test for *k* versus *k* + 1 profiles, *ALRT* Lo–Mendell–Rubin adjusted likelihood ratio test for *k* versus *k* + 1 profiles

Table 5 Fit indices for different latent profile solutions at measurement point 2

Profiles	#Par	LL	LL replicated	AIC	CAIC	BIC	SABIC	Entropy	VLMR	ALRT	Relative profile sizes
2	16	– 3059.1	Yes	6150.1	6230.4	6214.4	6163.6	0.761	< 0.001	< 0.001	0.59/0.41
3	22	– 2957.4	Yes	5958.8	6069.1	6047.1	5977.3	0.811	0.003	0.003	0.53/0.31/0.16
4	**28**	**– 2922.9**	**Yes**	**5901.8**	**6042.2**	**6014.2**	**5925.3**	**0.794**	**0.019**	**0.021**	**0.45/0.27/0.20/0.09**
5	34	– 2900.5	Yes	5869.0	6039.5	6005.5	5897.6	0.747	0.473	0.482	0.29/0.28/0.17/0.16/0.09
6	40	– 2881.5	Yes	5843.1	6043.6	6003.6	5876.7	0.777	0.351	0.357	0.32/0.26/0.16/0.11/0.09/0.05

The row set in bold corresponds to the model chosen for the analysis

#Par number of estimated parameters, *LL* log-likelihood, *AIC* Akaike Information Criterion, *CAIC* consistent AIC, *BIC* Bayesian Information Criterion, *SABIC* sample-size adjusted BIC, *VLMR* Vuong–Lo–Mendell–Rubin likelihood ratio test for *k* versus *k* + 1 profiles, *ALRT* Lo–Mendell–Rubin adjusted likelihood ratio test for *k* versus *k* + 1 profiles

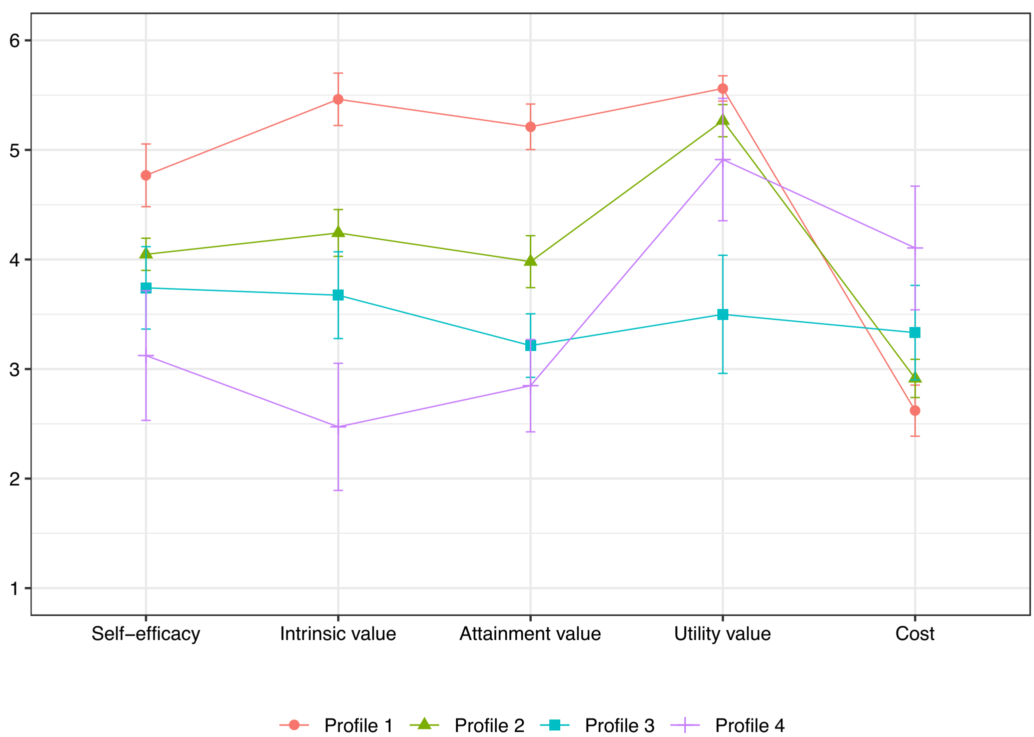

Fig. 1 Comparison of initial profiles. Error bars represent 95% confidence intervals

Table 6 Mean values (*M*) and standard errors (SE) of profile variables by initial profile

Construct	Profile 1		Profile 2		Profile 3		Profile 4		Variance
	M	SE	*M*	SE	*M*	SE	*M*	SE	
Self-efficacy	4.768	0.146	4.047	0.075	3.741	0.192	3.123	0.302	0.801
Intrinsic value	5.462	0.122	4.242	0.109	3.674	0.202	2.472	0.296	0.371
Attainment value	5.211	0.106	3.980	0.121	3.214	0.148	2.848	0.215	0.459
Utility value	5.561	0.059	5.267	0.075	3.499	0.275	4.912	0.285	0.365
Cost	2.620	0.119	2.914	0.089	3.332	0.220	4.105	0.288	0.976
Proportion	28.2%		51.6%		11.9%		8.3%		

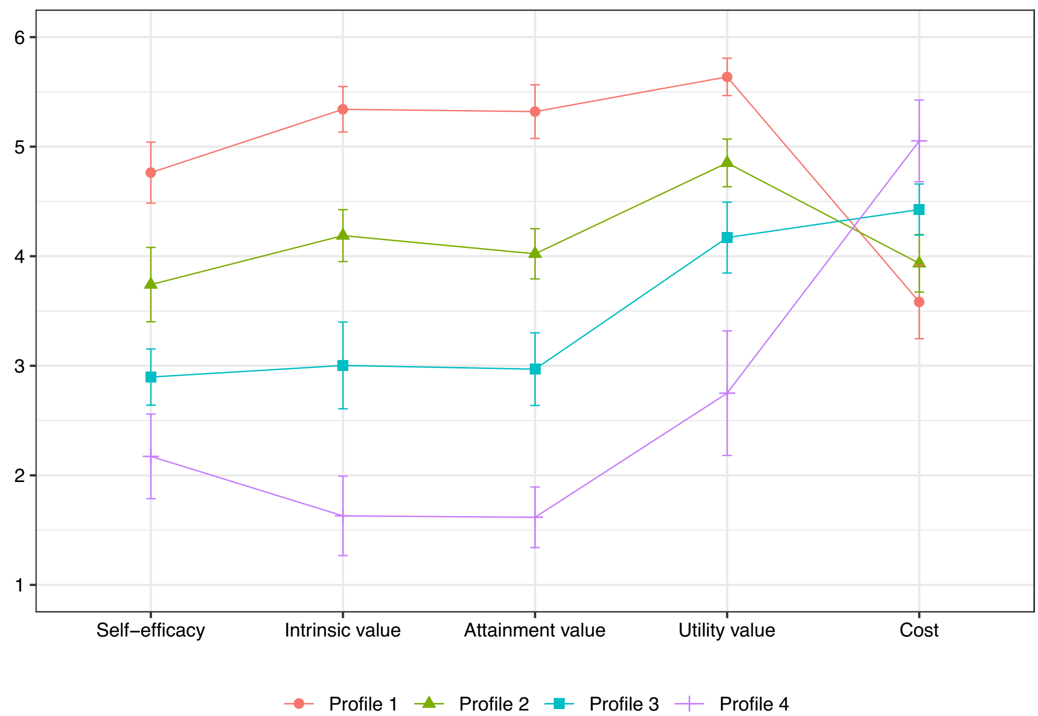

Fig. 2 Comparison of posterior profiles. Error bars represent 95% confidence intervals

(profiles 1 and 2) and two less adaptive profiles (profiles 3 and 4).

The exploration of posterior profiles resulted in profiles that can be compared well to the initial profiles. In general, the range of values of profile variables is larger in the posterior profiles than in the initial profiles (see Fig. 2).

Posterior profile 1 is comparable to Initial Profile 1 but shows higher cost (see Fig. 3). Therefore, we refer to this profile as the *high all except medium cost profile.*

Posterior profile 2 differs from Initial Profile 2 in that it exhibits higher cost and slightly lower utility value. We again refer to this profile as the *high extrinsic profile* (see Fig. 4).

Posterior profile 3 exhibits increased but still moderate utility value and cost compared to the corresponding initial profile (see Fig. 5). We again denote this profile as the *medium all profile.*

In Posterior profile 4, maladaptive manifestations in the corresponding initial profile have been reinforced. While expectancy as well as intrinsic, attainment and utility value beliefs have been reduced, cost has increased (see Fig. 6). We refer to this profile as the *low motivation, high cost profile.*

Profile transition

As can be seen from the proportion of students in each profile (Tables 6 and 7), the proportion of members of Profile 1 and Profile 2 has decreased considerably from MP1 to MP2, while that of Profile 3 has increased significantly. To gain a detailed insight into how students transition from the initial profiles to the posterior profiles, we display the transition probabilities and the proportions of profile members in Fig. 7; Table 8 provides additional information on the transition probabilities.

The probability of remaining in the posterior profile corresponding to one's initial profile is high in general with the exception of staying in Profile 4. Rather, the probability to change from Initial profile 4 to Posterior profile 3 is higher than the probability of remaining in Profile 4, even though not statistically significantly higher ($p = 0.312$). Moreover, the probabilities to transition to Posterior profiles 2 and 3 are substantial, in particular that of transitioning from Initial profile 1 to Posterior profile 2 ($p_{1,2} = 0.40$), which is, however, not statistically significantly lower ($p = 0.196$) than the probability of staying in Profile 1 ($p_{1,1} = 0.57$).

Initial profile membership by exam grade

The school leaving exam grades of students who completed the Austrian school leaving exam differ statistically significantly between the initial profiles ($\chi^2 = 49.07$, $df = 3$,

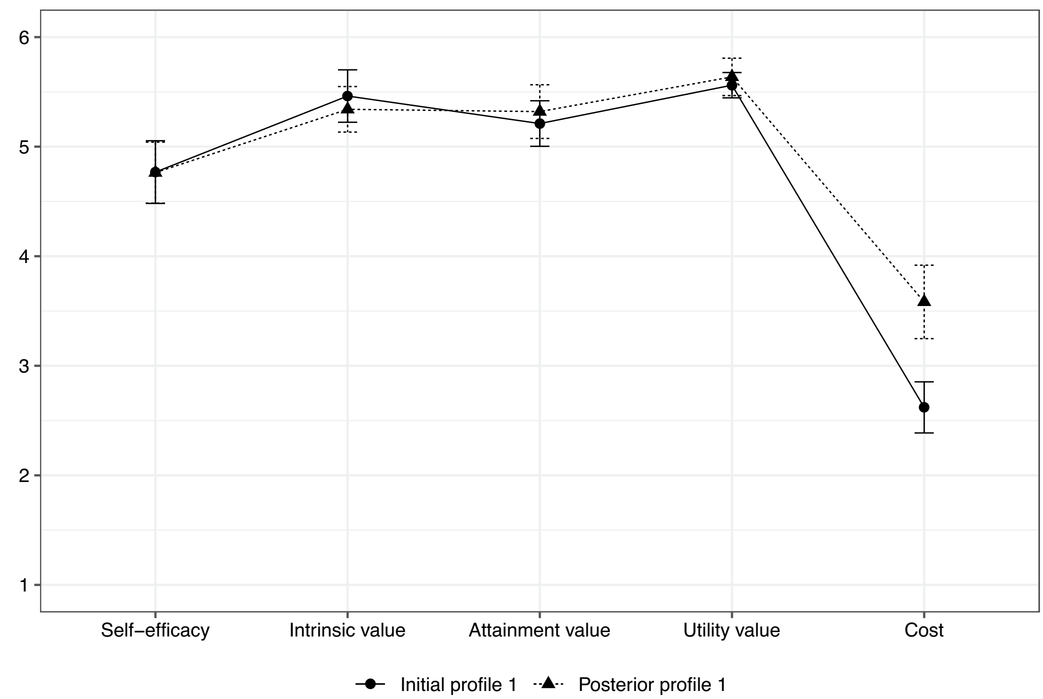

Fig. 3 Development of Profile 1. Error bars represent 95% confidence intervals

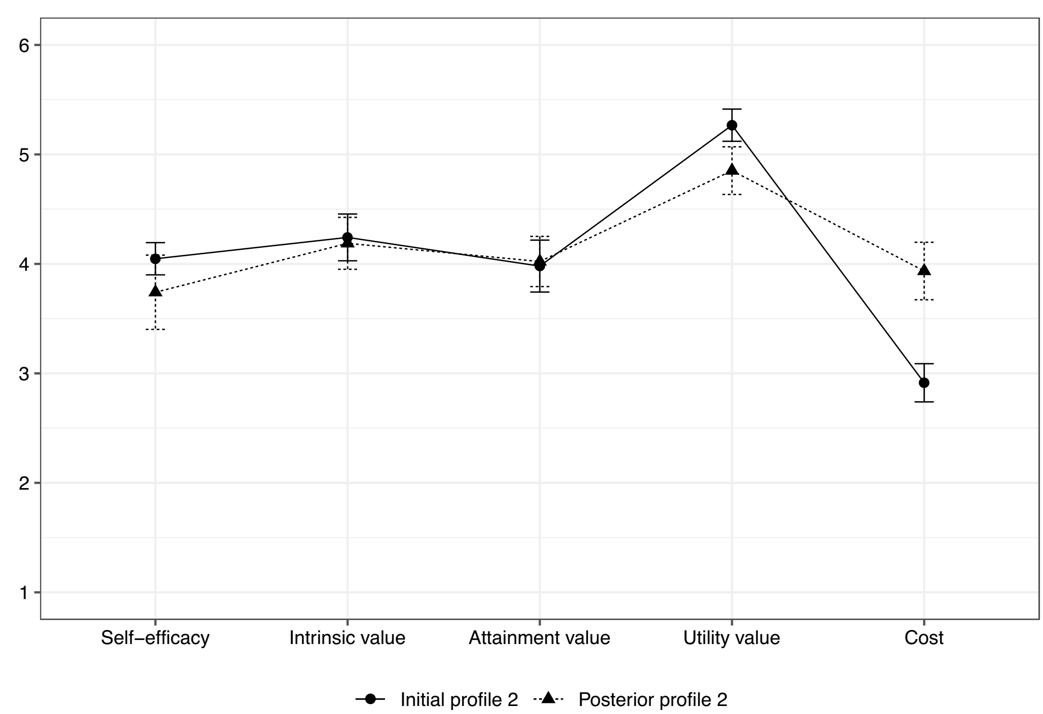

Fig. 4 Development of Profile 2. Error bars represent 95% confidence intervals

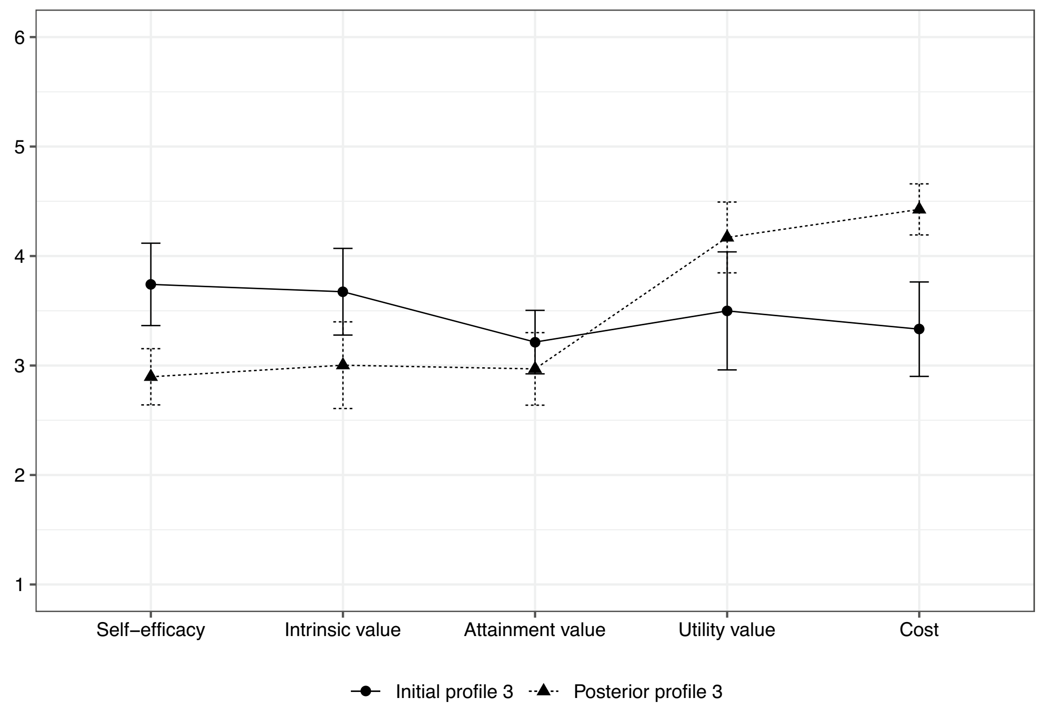

Fig. 5 Development of Profile 3. Error bars represent 95% confidence intervals

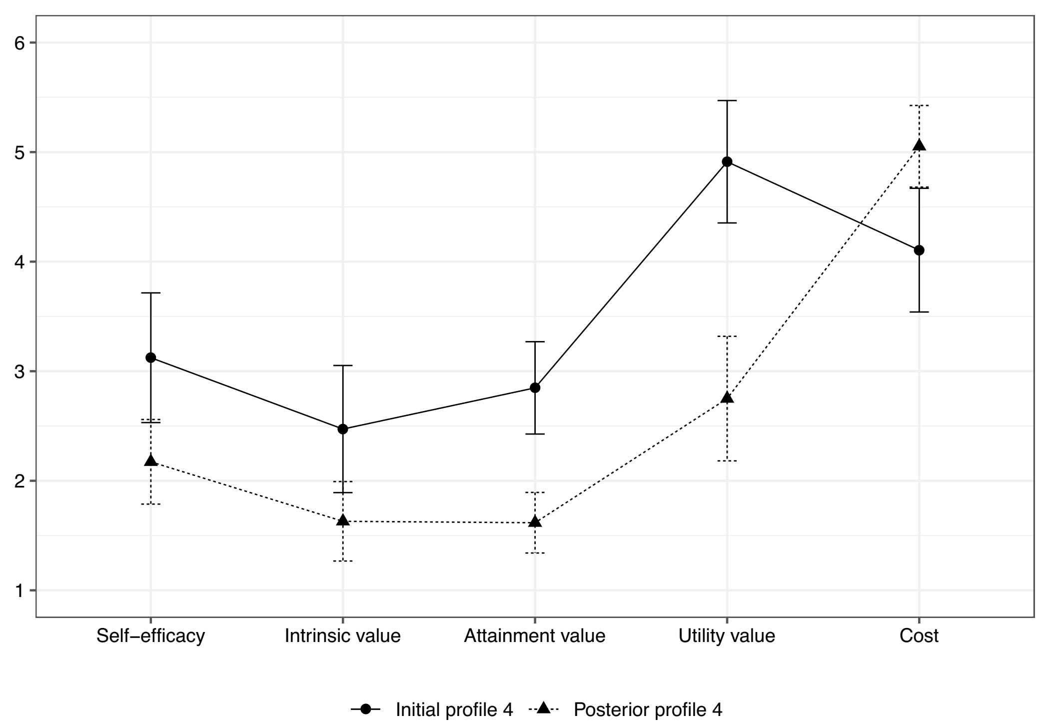

Fig. 6 Development of Profile 4. Error bars represent 95% confidence intervals

Table 7 Mean values (*M*) and standard errors (SE) of profile variables by posterior profile

Construct	Profile 1		Profile 2		Profile 3		Profile 4		Variance
	M	**SE**	***M***	**SE**	***M***	**SE**	***M***	**SE**	
Self-efficacy	4.763	0.142	3.741	0.173	2.897	0.131	2.173	0.197	1.086
Intrinsic value	5.341	0.106	4.188	0.121	3.003	0.202	1.630	0.185	0.442
Attainment value	5.320	0.125	4.022	0.117	2.969	0.169	1.617	0.141	0.346
Utility value	5.637	0.087	4.852	0.111	4.170	0.165	2.750	0.290	0.880
Cost	3.583	0.171	3.935	0.134	4.426	0.119	5.053	0.190	1.136
Proportion	18.3%		44.8%		27.1%		8.7%		

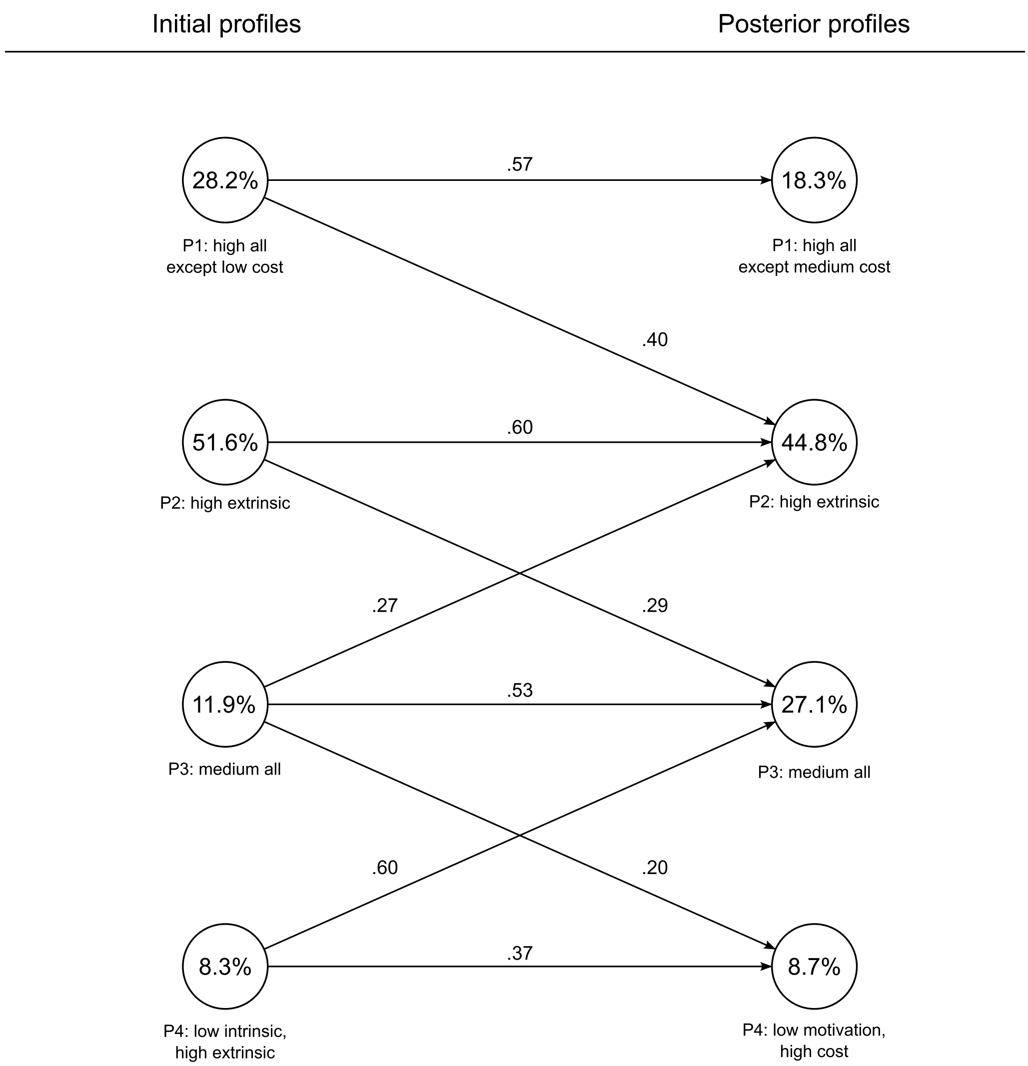

Fig. 7 Transition probabilities (>0.10) between initial profiles and posterior profiles

$p < 0.001$). Members of the more adaptive profiles had better grades in their final exams (see Table 9). Equality tests of means across profiles using the BCH procedure reveal that all the differences between the profiles are statistically significant except for the difference between Initial profile 2 and Initial profile 3 (see column "Comparisons" in Table 9).

Table 8 Probabilities and 95% confidence intervals for the transition from initial profiles to posterior profiles

	Posterior Profile 1	Posterior Profile 2	Posterior Profile 3	Posterior Profile 4
Initial Profile 1	0.573 [0.444, 0.693]	0.401 [0.274, 0.542]	0.024 [0.001, 0.314]	0.003 [0.000, 0.948]
Initial Profile 2	0.059 [0.023, 0.147]	0.595 [0.494, 0.689]	0.285 [0.206, 0.381]	0.060 [0.029, 0.120]
Initial Profile 3	0.000 [0.000, 0.000]	0.270 [0.123, 0.494]	0.528 [0.315, 0.731]	0.202 [0.088, 0.400]
Initial Profile 4	0.029 [0.003, 0.237]	0.000 [0.000, 0.000]	0.600 [0.377, 0.789]	0.371 [0.190, 0.597]

Table 9 Average grade (1 = highest, 5 = lowest) in the Austrian school leaving examination by initial profiles

Profile	Grade		Comparisons		
	Mean	SE		χ^2	*p*
1	1.419	0.090	Profile 1 vs. Profile 2	4.956	0.026
			Profile 1 vs. Profile 3	8.585	0.003
			Profile 1 vs. Profile 4	42.619	< 0.001
2	1.696	0.070	Profile 2 vs. Profile 3	2.113	0.146
			Profile 2 vs. Profile 4	28.651	< 0.001
3	1.969	0.166	Profile 3 vs. Profile 4	10.192	0.001
4	2.861	0.202			

$n = 347$

Table 10 Results from multinomial logistic regression of school type on profile membership

Variable	Category	Odds ratio	SE	95% Confidence interval	
Initial profiles					
Profile 1 (ref.)	–	–	–	–	–
Profile 2	ACAD (ref.)	–	–	–	–
	TECH	0.890	0.232	0.534	1.484
	OTHER	0.411	0.202	0.157	1.077
Profile 3	ACAD (ref.)	–	–	–	–
	TECH	1.576	0.618	0.731	3.398
	OTHER	1.469	0.910	0.436	4.946
Profile 4	ACAD (ref.)	–	–	–	–
	TECH	0.472	0.235	0.178	1.251
	OTHER	0.553	0.456	0.110	2.784
Posterior profiles					
Profile 1 (ref.)	–	–	–	–	–
Profile 2	ACAD (ref.)	–	–	–	–
	TECH	1.261	0.386	0.692	2.298
	OTHER	1.142	0.713	0.336	3.880
Profile 3	ACAD (ref.)	–	–	–	–
	TECH	1.359	0.450	0.710	2.601
	OTHER	1.888	1.190	0.549	6.495
Profile 4	ACAD (ref.)	–	–	–	–
	TECH	1.018	0.478	0.405	2.554
	OTHER	1.156	1.059	0.192	6.966

$n = 359$; *SE* standard error, *ACAD* Academic Secondary School (“Allgemeinbildende höhere Schule”), *TECH* Higher Federal Technical College (“Höhere technische Lehranstalt”), *OTHER* other school types

Initial and posterior profile membership by school type

The great majority of participants (87.7%) obtained their permission for higher education in Austria. Results from multinomial logistic regression of the school type on profile membership (see Table 10) reveal that the odds of students from Higher Federal Technical Colleges to be in Initial profile 3 rather than in Initial profile 1 were 1.58 times the odds of academic secondary school students. Contrary to that, the odds of students from Higher Federal Technical Colleges to be in Initial profiles 2 or 4 rather than in Initial profile 1 were 0.89 times and, respectively, 0.47 times the odds of academic secondary school students.

Regarding posterior profile membership, the odds of students from Higher Federal Technical Colleges were higher for being in Posterior profile 2 (1.26 times that of academic secondary school students), in Posterior profile 3 (1.36 times that of academic secondary school students), or in Posterior profile 4 (1.02 times that of academic secondary school students) rather than in Posterior profile 1. We note that the odds ratios are not statistically significantly different from 1 (95% confidence interval).

Posterior profile membership by exam score

Among the participants who completed the final exam of the preparatory course ($n = 196$), we observed statistically significant differences in the exam scores between the profiles ($\chi^2 = 8.057$, $df = 3$, $p = 0.045$). Using the BCH procedure for equality tests of means across posterior profiles, we found that the exam results were statistically significantly higher in profile 1 than in profile 2 and profile 3 (see Table 11).

Checks for selection effects

As for potential selection effects (see Appendix B), the data showed that the 409 students who participated at both measurement points had statistically significantly more favorable intrinsic value beliefs ($t = 3.81$, $df = 697$,

Table 11 Mean relative score (0–1) in the final exam of the preparatory course by posterior profiles

Profile	Exam score		Comparisons		
	M	SE		χ^2	*p*
1	0.672	0.026	Profile 1 vs. Profile 2	6.206	0.013
			Profile 1 vs. Profile 3	4.300	0.038
			Profile 1 vs. Profile 4	2.420	0.120
2	0.577	0.024	Profile 2 vs. Profile 3	0.000	0.986
			Profile 2 vs. Profile 4	0.307	0.579
3	0.578	0.038	Profile 3 vs. Profile 4	0.180	0.671
4	0.601	0.037			

$n = 196$, *M* mean, *SE* standard error

$p < 0.001$), attainment value beliefs ($t = 3.55$, $df = 692$, $p < 0.001$), and utility value beliefs ($t = 2.26$, $df = 555.39$, $p = 0.024$), as well as lower cost ($t = -2.71$, $df = 695$, $p = 0.003$) at MP1 compared to those 301 students who participated only at MP1. Self-efficacy did not differ statistically significantly between these groups ($t = 0.60$, $df = 608.73$, $p = 0.549$). The two groups did not differ statistically significantly in age ($t = -1.65$, $df = 666$, $p = 0.100$) or gender ($\chi^2 = 1.388$, $df = 1$, $p = 0.239$). These observations indicate a positive selection of students who were initially in a better position than those who did not participate at MP2. We take up these selection effects and their potential influence on our results in the discussion.

Discussion

In this work, we have gone well beyond observing general trends in the self-beliefs of students at the secondary–tertiary transition which we reported in a recent paper using the same dataset (Mayerhofer et al., 2023). We have identified the prevalent patterns of self-beliefs held by STEM field students during their first semester at university. Our person-centered approach enables us to describe the development of these self-beliefs in terms of transition probabilities between initial and posterior expectancy-value profiles. All profiles exhibit a stable or negative development of expectancy-value beliefs as well as a steep increase in cost.

Resulting initial profiles. The four resulting initial profiles show that the students' self-efficacy, intrinsic value, and attainment value beliefs are all comparably high within each profile. Profiles with high such beliefs correspond to low cost and vice versa. The profiles differ primarily in terms of the level of these beliefs. Interestingly, there are two profiles, the high extrinsic profile (Initial profile 2) and the low intrinsic, high extrinsic profile (Initial profile 4), in which utility value is considerably higher compared to the level of the other beliefs. The students in these two profiles seem to draw their motivation to pursue a STEM field degree program primarily from how they perceive the utility of mathematics for their professional future. High utility value of students in Initial profile 2 is accompanied by sound intrinsic motivation and value of learning mathematics. Notably, this profile accounts for more than half of the sample. The strong perception of the utility of mathematics did not show in profiles of students in grades 6 to 8 (Schweder & Raufelder, 2022), in grades 9 to 10 (Lazarides et al., 2022), or in grade 11 (Fong et al., 2021). We suspect that this perception of the utility of mathematics is a result of considerations of employment prospects at the end of their schooling and might therefore be particularly present at the transition to university. Initial profile 4 was similar to the hypothesized profile low in expectancy and intrinsic value beliefs (H1b) but had high instead of the hypothesized low extrinsic value beliefs and moderate instead of high cost. The make-up of this profile suggests that these students, compared to those in initial profile 2, draw their learning motivation even more from extrinsic incentives such as job aspirations rather than from interest in mathematics. According to the self-determination theory of Deci and Ryan (2015), such extrinsic aspirations correlate with poor psychological health. This could be an explanatory factor for university dropout. Beyond that, low mathematics self-efficacy has been shown to be strongly related to math anxiety (Rozgonjuk et al., 2020) which additionally nurtures dropout intentions.

The initial profiles include the high all except low cost profile, as hypothesized (H1a). Among the four profiles, we consider students in the high all except low cost profile to be in the best position to master the secondary–tertiary transition. From a psychological and developmental point of view, it is desirable for self-efficacy, intrinsic value, and attainment value to be high and for cost to be low.

In Initial profile 3, the manifestation of all measured constructs is moderate. There is no strong tendency either towards more or towards less favorable patterns of self-beliefs.

Resulting posterior profiles. The four posterior profiles that have emerged from the latent profile analysis exhibit greater differences in the profile variables than the initial profiles. This suggests that the self-beliefs of students are initially more uniform or indifferent and then become more varied and explicit in the course of the secondary–tertiary transition.

Posterior profile 1 is highly comparable to Initial profile 1, exhibiting high expectancy and value beliefs and moderate cost. Notably, and different from hypothesis (H1d), cost has increased substantially over time. This is most likely due to higher expectations at university than at school and due to a better understanding as well as a more realistic assessment of the requirements at university. Similarly, profile 2 is stable except for an increase in cost.

Posterior profile 3, besides an increase in cost, exhibits a sharp increase in extrinsic value beliefs, suggesting that the initially indifferent manifestation of intrinsic and extrinsic value beliefs develops in favor of extrinsic beliefs.

While profiles 1, 2, and 3 are essentially stable in expectancy and intrinsic value beliefs, the manifestation of these aspects decreases significantly in Posterior profile 4 compared to the respective initial profile. Cost increases, as in all the other profiles. The increase in cost among first-semester students has also been observed among undergraduate biology students (Perez et al., 2019a). Profiles comparable to the posterior profiles of our study have also been identified among first-semester chemistry students in their third month at a Canadian university with the exception of the low motivation, high cost posterior profile (Lee et al., 2022).

Interestingly, among the posterior profiles, there is no profile showing particularly high extrinsic value beliefs. This is surprising since, according to Deci and Ryan (2015), one would expect that intrinsic motivation is compromised by deadlines and other requirements to proceed further into the degree, which should lead students to adopt extrinsic aspirations, specifically on the utility of a mathematics degree for future employment. Posterior profile 3 comes closest to reflecting this hypothesized pattern (H1c).

Development of profiles. Our results indicate that the profiles remained either stable or developed unfavorably between the two waves. The more adaptive profiles (profiles 1 and 2) maintained the high level of expectancy and value beliefs, while cost increased noticeably. The less adaptive profiles (profiles 3 and 4) underwent significant negative changes. The general negative trend of expectancy may well be accounted for by the big-fish-little-pond effect. As in Perez et al. (2019a), we see that the overall negative trend in value beliefs and cost is driven by the strong deterioration in students with maladaptive initial beliefs. These trends are the more worrisome considering that nonparticipation of students at measurement point 2 resulted in a positively selected sample of students with higher initial value beliefs and better grades in their school leaving examination. This means that the students included in this study are a selection of students who, on average, were already in a desirable motivational starting position. It can be assumed that a considerable proportion of the students who did not participate in the second wave had already dropped out of their respective degree programs.

Transition from initial to posterior profiles. While the students of all initial profiles (except for Initial profile 4) are most likely to remain in a profile comparable to their initial profile, there is a considerable probability to change to a different profile over time. The results of our study clearly indicate that changes of profiles are mostly towards Posterior profiles 2 and 3: There is a 40% probability of changing from Initial profile 1 and a 27% probability of changing from Initial profile 3 to Posterior profile 2. These probabilities do not differ statistically significantly from staying in Profile 1 or, respectively, Profile 3 and are therefore relatively high. The chance of transitioning from Initial profile 2 to Posterior profile 3 is 29% and thus significantly lower than that of staying in Profile 2. Students in Initial profile 4, in turn, are 60% likely to transition to Posterior profile 3. The likeliness of transitioning to the Posterior profiles 1 and 4 is, for the most part, insignificantly small. Overall, there is a strong tendency that students either transition to the posterior profile that corresponds to their initial profile or to transition to the Posterior profiles 2 and 3.

Prior achievement in initial profiles. We have used the grades in the Austrian centralized school leaving exam in mathematics as a proxy for prior achievement. We have found that better grades in this exam correspond to more adaptive initial expectancy-value patterns. The differences in the grades are statistically significant for all initial profiles except for the difference between Initial profiles 2 and 3. This suggests that the mathematics grade in the Austrian school leaving exam positively predicts adaptive expectancy-value patterns and, for the most part, confirms our hypothesis (H2a).

School types in initial and posterior profiles. Our data allowed for comparisons between academic school students and students from Higher Federal Technical Colleges. Since expectancy-value beliefs have been found to be higher among academic school students than among students from vocational schools in their final year at school (Trautwein et al., 2012), we had expected differences in the initial profiles in favor of students having graduated from academic secondary schools (H2b). While there is no apparent tendency in the initial profiles speaking in favor of students from either school type, the results provide some indication that academic school students are more likely to be in the most adaptive posterior profile. This might reflect outcomes from the orientation of upper secondary schools to foster learning strategies and learners' self-beliefs while Higher Federal Technical Colleges provide more specialized education. Since these trends are not statistically significantly different among different school types, they do not fully contradict our hypothesis (H3a).

Academic achievement in posterior profiles. We have used the score in the final exam of the preparatory course as a proxy for achievement in university mathematics. The correlation between the grade in the mathematics school leaving exam and the final exam of the preparatory course suggests that students with better grades in the school leaving exam also achieve better results in the exam of the preparatory course. This relationship appears to be of a small but remarkable effect size and indicates that the achievement in mathematics is to a certain degree stable when comparing assessments at school and at university. In line with our hypothesis (H3b), we have found that better results correspond to more adaptive posterior profiles. No statistically significant differences between profile 4 and the other profiles were found. This may be due to the small number of participants in this profile who had given consent that their exam scores be processed. Reasonable explanations could be that students in this group did not participate in the final exam of the preparatory course, which would be in line with the low manifestation of motivation in this profile, or that these students geared their strategies towards achieving the best possible score while neglecting their progress in mathematics. Overall, the observed relationship between the expectancy-value profiles and the exam score supports the conclusion of Trautwein et al. (2012) that expectancy-value profiles would predict academic achievement.

Limitations and future research

Notwithstanding the contributions of this work, several potential limitations should be kept in mind when interpreting our findings. First, the period between the two measurement points are the first two months of students studying at university. In this period, the students are affected by many different influences, some of which are related to their general life transition rather than to the transition in their educational career. The second measurement point was two months into the first semester so that the period between the two measurement points was short enough to avoid positive selection due to student dropout, for example, because of performance issues and experience of failure, and long enough to capture the trends appearing at the secondary–tertiary transition. This compromise has allowed us to observe meaningful trends while minimizing potential biases.

Second, we chose to run the analysis of latent profiles at MP2 independently of the profiles found at MP1, i.e., the profile variables at MP2 could have mean values and variances different from the corresponding profile variables at MP1, since we aimed to capture the development of profiles over time. This, however, required us to match the initial profiles with the posterior profiles qualitatively using the mean values and variances of the profile variables as indicators.

Third, to derive implications from our results, it seems reasonable to put the profiles in an order. We ordered the profiles by how desirable they are from a psychological perspective. While the order among the posterior profiles can be derived rather directly from the levels of manifestations of the profile variables (see Fig. 2), the order of initial profiles is not unambiguous due to the higher utility value in profile 4 compared to profile 3 while all other variables indicate that profile 3 could be considered more desirable than profile 4, which was decisive for our decision on the order of profiles.

Another limitation is that, for assessing prior achievement, we have only included self-reported grades in the Austrian school leaving exams. Since nearly 90% of the participants graduated from schools in Austria, these grades are, however, sufficiently representative for the whole sample.

In addition, since all participants of our study are students of the same institution, checks for specific institutional effects on our results are not possible.

Finally, it should be noted that the assessment of achievement is based on a mathematics exam that is part of the preparatory course, which most of the participants took at the end of the preparatory course, before the start of their first-semester courses. The scores of these exams can yet be considered as approximately indicative of academic achievement since they reflect to what degree the students were able, on the one hand, to transfer their mathematics knowledge from school to an assessment of their mathematics knowledge at university, and, on the other hand, to adapt to the nature of assessments at university. It remains a desideratum for future research to investigate how academic achievement and persistence develop in the long term in the respective profile.

Since the overall socio-economic background of schools has been found to be related to academic achievement (e.g., Rozgonjuk et al., 2023), it would be worthwhile to investigate whether the socio-economic background of the school continues to have an effect on achievement at university.

Conclusions

Our study shows that opportunity cost increases sharply at the secondary–tertiary transition across all profiles. While this is not unexpected because students are still adjusting to higher demands on their commitment and their performance at university, it is important for institutions to recognize these effects and implement measures to keep the motivation of their students high. The utility of mathematics for their professional future is a manifest source of motivation in three of the four student profiles. To maintain this source of motivation, we conclude that the high relevance of mathematics in professional applications should be stressed where possible. Utility-value-based interventions have proven to be effective (see, e.g., Soicher & Becker-Blease, 2023) and could, if integrated into first-semester courses, be a valuable resource for students in STEM fields.

Finally, institutions should pay attention to the further deterioration in self-efficacy and beliefs related to intrinsic motivation of students who hold low such beliefs about themselves upon arrival at university. Students, in particular those with maladaptive initial motivational patterns, should have ample opportunities to earn a sense of accomplishment. This would strengthen their self-efficacy, which is vital for students to persist in their degree programs.

Appendix A: Procedure of conducting latent profile analysis

Latent profile analysis is an exploratory approach; however, there is a range of indicators helping to narrow down the number of options for deciding on a model. Latent profile analysis is based on estimating model parameters using the maximum likelihood method which iteratively computes and optimizes parameter values to arrive at those values which best describe the data. *Best* in this sense means that the likelihood of the data to fit the model is maximized. To avoid arriving at a local maximum, the algorithm uses different starting values to increase the chance that the identified maximum is the global maximum of the log-likelihood function. For carrying out this procedure in *Mplus 8.8*, we chose the robust maximum likelihood estimator (Mplus syntax: `ESTIMATOR IS MLR`) and specified the number of starting values to be 500, the number of optimization steps to be 100 (`STARTS ARE 500 100`), and the number of initial stage iterations to be 50 (`STITERATIONS IS 50`). The procedure was carried out iteratively with an increasing number of profiles, starting with two profiles and going up to six profiles. Each of these steps produced several parameters indicating the goodness of model fit. In deciding on a model, we first excluded models that did not converge at a maximum or whose maximum log-likelihood value was not replicated (suggesting that the identified maximum is a local maximum and not the global maximum). We also required the entropy of the model to be at least 0.70 and each profile to contain at least 5% of the total sample. We selected the final model based on information criteria (AIC, CAIC, BIC, SABIC), with the Bayesian Information Criterion (BIC) being the most significant. The model with the lowest BIC value of all the potential models with a BIC difference less than 10 compared to the model with the next highest number of profiles was selected as the final model. The remaining information criteria were used as indicators of plausibility of this choice. This procedure was performed separately for each measurement point and resulted in a model consisting of four profiles at each measurement point, respectively.

To enable multinomial logistic regression analysis, we recoded the variable containing the school type into dichotomous variables, i.e., the seven different values of the school type variable were split into three variables which reflect whether or not (0 = no, 1 = yes) students attended an academic secondary school, a Higher Federal Technical College or a school of a type other than these two. The remaining school types were merged due to low occurrence. Since Mplus uses by default the last category (i.e., profile 4) of the categorical latent variable as the reference category, we recoded the values representing the profiles for this step into the dropped order so that we could use profile 1 as the reference category in multinomial logistic regression analysis.

Appendix B: Attrition and related descriptive statistics

Out of the 710 students participating at MP1, the 409 students who participated also at MP2 were the basis for data analysis. Table 12 provides an overview on how many students participated only at MP1 (see column "MP1") or both at MP1 and MP2 (see column "MP1 & MP2"). The results of independent *t*-tests in Table 12 show that those who participated in both waves initially had statistically significantly higher value beliefs and lower cost, and had statistically significantly better grades in their school leaving examination.

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Author contributions
Conceptualization: ME, ML, MM; methodology: ML, MM; formal analysis and investigation: ML, MM; writing—original draft preparation: MM; writing—review and editing: ME, ML; supervision: ME, ML.

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Availability of data and materials
The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Table 12 Descriptive statistics of students who participated only at MP1 or both at MP1 and MP2

	MP1	MP1 & MP2	*t*	*df*	*p*	Overall
n	301	409				788
Self-efficacy (MP1)	4.09 (1.11)	4.14 (1.01)	0.60	608.73	0.549	–
Intrinsic value (MP1)	4.05 (1.17)	4.37 (1.04)	3.81	697.00	< 0.001	–
Attainment value (MP1)	3.85 (1.11)	4.14 (1.02)	3.55	692.00	< 0.001	–
Utility value (MP1)	4.95 (1.01)	5.11 (0.87)	2.26	555.39	0.024	–
Cost (MP1)	3.20 (1.08)	2.98 (1.07)	− 2.71	695.00	0.003	–
Age	20.25 (2.78)	19.87 (2.95)	− 1.65	666.00	0.100	20.03 (2.82)
Gender (1 = male, 2 = female)	1.29 (0.45)	1.28 (0.48)	− 0.36	661.00	0.716	1.26 (0.44)
Year of graduation	2020.55 (2.58)	2020.88 (2.65)	1.60	666.00	0.111	2020.74 (2.57)
Grade in school leaving exam (1–5)	2.20 (1.06)	1.75 (0.89)	− 5.18	404.49	< 0.001	1.91 (0.97)
Prior university experience (1 = yes)	0.86 (0.35)	0.89 (0.32)	0.95	668.00	0.343	0.87 (0.33)
University experience in family (1 = yes)	0.77 (0.42)	0.75 (0.43)	− 0.62	668.00	0.536	0.76 (0.43)

Except for the row showing the number of participants ("*n*"), the values in the columns "MP1" and "MP1 & MP2" are mean values followed by standard deviations in parentheses

Declarations

Ethics approval and consent to participate

Participation in this study was voluntary and subject to informed consent of the participants.

Competing interests

The authors declare that they have no competing interests.

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