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# Cultural Diversity in Academic Motivation: Universality and Model Complexity

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## ABSTRACT

This contribution centres on two interconnected conjectures. The first posits that motivational—and the way we model what influences motivation— can be significantly enhanced by integrating the concept of growth orientation. This integration enables to connect growth mindset frameworks and motivational theories through straightforward antecedent-consequence models. The second conjecture is that simpler models tend to vary less and are more stable across different groups compared to more complex models. An example brings these two conjectures together by analysing cultural differences in academic motivation. It compares three models using data from international students studying mathematics and statistics: (1) a comprehensive growth orientation model incorporating both global and specific factors, estimated using Bifactor Exploratory Structural Equation Modelling (B-ESEM); (2) a simplified version of this model with growth orientation as the sole antecedent factor; and (3) a Structural Equation Model (SEM) using specific factors as antecedents. In the illustrative example, the degree of cultural diversity in motivational levels is found to be relatively small, comparable in magnitude to gender differences. However, more complex antecedent-consequence models can easily lead to the conclusion that significant diversity exists between cultural groups. Our findings challenge common assumptions about the cultural specificity of academic motivation models and highlight a promising yet often overlooked factor for building robust explanations of learning motivation: students' growth orientation.

***Keywords:*** Academic Motivation; Cultural Diversity; Growth Orientation; Model Complexity; B-ESEM

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# 1. Introduction

The discussion surrounding cultural diversity—both in general and specifically in student academic motivation—spans a spectrum from universalism to relativism, fundamentally reflecting differing cultural theories. McInerney[1] (see also[2]), a proponent of cultural relativism, examines cultural diversity through motivational principles such as self-regulation, goal setting, and the role of individual feedback, emphasizing their varying functionality across cultures. At the other end of the spectrum, Soenens and Vansteenkiste[3] adopt a universalistic perspective grounded in self-determination theory (SDT[4]). This framework identifies need satisfaction and need frustration as universal drivers of motivational processes.

Our contribution aims to complement this theoretical lens on cultural diversity with a methodological perspective. Specifically, we argue in this paper that the observed diversity in psychological processes modelled empirically may partly—or entirely—stem from the complexity of the models themselves. In simpler terms, cultural differences highlighted by complex models might diminish or disappear when simpler models are employed, following the principle of parsimony (or Occam's Razor), which suggests that models should not be more complex than necessary to explain or predict data.

We illustrate this argument by focusing on models centred on the concept of growth orientation. Although growth orientation is rooted in established theoretical frameworks of psychological growth—such as Dweck's[5] self-theories-based meaning system and Ryan and Deci's[4] self-determination theory—its application in empirical models of motivational processes is relatively recent. This is largely due to the emerging use of advanced statistical techniques, such as Bifactor Exploratory Structural Equation Modelling (B-ESEM[6, 7]), which is still in the process of becoming a well-established tool in the methodological repertoire of our field. Recent empirical work by Bostwick et al.[8–10] and Martin[11, 12] reflects this growing interest in growth-orientation-based models. We propose that incorporating the concept of growth orientation into theoretical frameworks of academic motivation is a highly promising yet underexplored[10] advancement, that aligns with Maehr's[13] first strategy for predicting academic motivation through culture: culture predicts personality predicts motivation.

The remainder of this introduction is structured as follows. We begin by outlining how this study addresses cultural diversity, drawing on Hofstede's national cultural value dimensions[14–17], which serve as the basis for creating cultural clusters through latent profile analysis. We then introduce the growth-orientation framework of learning motivation[8–12], along with the key motivational theories that inform this integrative approach: mindset theory (including effort beliefs), self-determination theory, and goal-setting theory, with a particular focus on future-oriented goal setting. The integrative nature of the growth-orientation framework allows for a comparison between models of varying complexity—ranging from simpler models based solely on global growth orientation to more complex models incorporating all specific contributing factors. This issue of model complexity is addressed in the final part of the introduction.

## 1.1. Cultural Diversity

In the characterization of cultural differences by means of quantitative descriptions, Hofstede's research[14–17] holds a prominent position. Through an analysis of attitude surveys from employees across over 50 countries, Hofstede identified six primary value dimensions where cultures diverge: power distance, uncertainty avoidance, individualism–collectivism, masculinity–femininity, long-term–short-term orientation, and indulgence–restraint.

Power distance concerns the acceptance of unequal power distribution by less powerful members in organizations and institutions. Uncertainty avoidance reflects a society's tolerance for ambiguity and indicates how much uncertainty members of a culture find threatening. Individualism versus collectivism indicates the degree to which individuals are integrated into groups—from loose ties with emphasis on self-reliance to strong cohesive in-groups. In masculine societies, distinct gender roles are emphasized, while feminine societies show more overlap in these roles. Long-term orientation distinguishes societies oriented towards future rewards versus immediate needs fulfilment. The indulgence versus restraint dimension, the newest addition, signifies a culture's permissiveness or restriction regarding gratification of human desires related to hedonism and consumerism.

Although initially aimed at studying how cultural differences affect leadership styles, Hofstede's dimensions also impact learning and teaching styles[17, 18]. Particularly influential is the masculinity–femininity dimension: in strongly masculine countries like Germany and Japan, education emphasizes competition, striving openly for excellence, elevating top students as the standard, and viewing failure as a significant setback. In contrast, in "feminine" countries like the Netherlands and Nordic European countries, the focus is on the average student, keeping excellence more private, and seeing failure as a learning opportunity [17]. Other dimensions play lesser roles; for example, long-term orientation generally benefits educational outcomes, particularly in mathematics.

In collectivist societies, education tends to focus on preparing youth for societal participation with great emphasis on diplomas and certificates. Conversely, individualistic societies emphasize learning how to learn. Students from high uncertainty-avoidance countries prefer structured learning with clear objectives and expert teachers, whereas those from low uncertainty-avoidance countries prefer open-ended learning environments where teachers may acknowledge uncertainty [17].

These cultural value dimensions influence educational systems' optimal design, aligning educational paradigms such as student-centred learning with societies characterized by low power distance and weak uncertainty avoidance—like the Netherlands, Nordic European, and Anglo-Saxon countries. Conversely, teacher-centred education suits contexts with high power distance and strong uncertainty avoidance, prevalent in Eastern European and Latin countries. Motivating students through individual competition tends to be most effective in masculine, individualistic societies like the USA and German-speaking countries, compared to more feminine and egalitarian societies such as the Netherlands and Nordic European countries [17]. These examples illustrate that cultural diversity transcends geographical distance, evident in the distinct characteristics of societies like those of Dutch and German origin. Studies that categorize countries based on cultural value dimension scores into clusters with relatively homogeneous cultural values, such as the GLOBE study [19], highlight Europe as a striking example of cultural diversity: five out of the ten identified global cultural clusters are found within Europe.

Hofstede's theory of cultural value dimensions can be positioned within Bronfenbrenner's bioecological model of human development [2, 20], which has gained traction in educational psychology research [21, 22]. The bioecological model outlines five nested systems that shape human development: the microsystem, mesosystem, exosystem, macrosystem, and chronosystem [22]. Among these, the macrosystem serves as a "blueprint" for the development of the inner systems, influencing individual dispositions in students, such as achievement motivation. According to Hofstede's framework [17], cultural value dimensions are a fundamental element of this blueprint, exerting a significant influence on the inner systems and positioning themselves as potential antecedents of academic motivation. This perspective implies that national-level, rather than individual-level, scores for cultural value dimensions should guide empirical modelling.

## 1.2. Growth Orientation

In the context of educational psychology, growth orientation is a multifaceted concept that integrates various motivational theories directed at personal growth. Empirical studies on growth orientation, particularly by Australian researchers as Bostwick et al. [8–10] and Martin [11, 12], define growth orientation using a framework of two types of achievement goals: task-based growth goals and self-based growth goals [23, 24], along with the concept of growth mindset [5].

However, the theoretical discussions within these same research works often encompass a broader range of motivational theories related to growth. For example, Martin et al. [12] highlight four major motivational theories that emphasize growth: achievement goal theory, goal-setting theory, self-determination theory, and self-concordance theory. This list was further expanded in Martin's later work [11], which added flow theory as additional growth-oriented frameworks.

### 1.2.1. Self-Determination Theory

A key theme in all discussions of growth-related motivational theories, beyond the specific focus on growth goals and mindsets, is the central role of self-determination theory [4]. This theory, particularly its concept of autonomous motivation, is consistently presented as a core growth-oriented construct. In our illustrative example, we therefore opt for the inclusion of self-determination theory in an expanded operationalization of growth orientation, reflecting its importance in providing a more comprehensive understanding of motivational processes that foster personal growth.

### 1.2.2. Future-Based Goal Setting

Another feature of our example is to address the challenge posed by Bostwick et al.[10] and Martin[11] in confirming the presence of growth orientation while adopting a different framework for self-based goals, beyond the concept of personal-best goals[25]. Specifically, we focus on the role of growth orientation when potential-based goals[24] are used as the operational definition of growth goals instead.

### 1.2.3. Effort Beliefs

A third innovation regards highlighting a highly undervalued aspect of the mindset framework: effort beliefs grounded in views of intelligence. Although developed by Blackwell and Dweck[26], only a few empirical studies within the mindset framework have utilized these powerful mediators in examining the relationships between mindsets and learning dispositions.

Adopting these innovations in growth orientation modelling moves us closer to an investigation of Dweck's[5] self-theories-based meaning system. In this meaning system, students form self-beliefs about the nature of intelligence, the role of effort in learning, the nature of their motivation, and the future perspective of the goals they set for learning. These beliefs tend to align as either adaptive—supporting growth and learning—or maladaptive, where the focus is on appearing smart rather than truly learning.

## 1.3. Specific Factors of Growth Orientation

### 1.3.1. Growth Mindsets

Growth mindsets form the foundation of a growth-orientation to learning. These concepts have existed since the 1980s under different terminology[5, 27], later described more intuitively as "growth" and "fixed" mindsets[28]. Originally referred to as implicit theories of intelligence, these encompass two opposing self-theories: the incremental theory, holding that intelligence is malleable, and the entity theory, suggesting that intelligence is fixed and unchangeable. Students with a growth mindset believe they can improve their intelligence through effort and practice, whereas those with a fixed mindset view intelligence as more static and difficult to change[5]. In Dweck's work, these theories are embedded within a broader "meaning system" framework, which posits that individuals develop beliefs that shape their understanding of the world and give meaning to their experiences. Dweck's "meaning system approach" focuses on self-theories—beliefs about oneself—that include implicit beliefs about intelligence, effort, goal-setting, intrinsic and extrinsic motivation, and self-regulation strategies[5]. In expanding the concept of growth orientation, we aim to build upon these foundational ideas of a meaning system grounded in self-theories.

### 1.3.2. Growth Goals

Martin's development of personal best (PB) goals[23, 25] was an early effort to explicitly incorporate a growth dimension into achievement goal setting. Personal best goals focus on personal growth by aiming to exceed or match one's previous best performance, forming the foundation for subsequent research on growth goal setting[8–12]. Later work, particularly within the AGQ framework by Elliot et al.[24], offered another perspective. The AGQ framework initially defined achievement goals through two components of competence: definition and valence. "Definition" determines the standard of competence assessment, categorized as task-/self-based (mastery) or other-based (performance), while "valence" indicates whether the goal centres on the potential for success (approach) or the possibility of failure (avoidance). The 3x2 AGQ model[29] includes mastery goals encompassing task- and self-based intrapersonal standards and performance goals relying on other-based interpersonal standards. In this structure, self-based goals referenced past performance. In[24], Elliot et al. introduced growth orientation as a novel approach to past-based standards, focusing instead on proving one's potential. This led to a future-oriented, growth-based version of intrapersonal goal setting, known as "potential-based" goals, which include both approach and avoidance dimensions.

### 1.3.3. Effort Beliefs

Early research on the impact of self-theories' meaning systems on learning highlighted the importance of students' beliefs about effort in learning[5, 30]. Students with a growth mindset generally view effort as positive, seeing hard work as essential for improving ability. In contrast, students with a fixed mindset tend to view effort negatively, believing that it signals low ability to others and obstructs appearing intelligent to peers. The significance of these effort beliefs was empirically supported by studies from Blackwell[26, 30].

However, few studies have built upon these findings, a notable exception being [31], which demonstrated the critical role of effort beliefs in mediating the relationship between mindsets and learning performance.

#### 1.3.4. Self-Determination Theory

The final component of Dweck's meaning system integrated into this study is the distinction between adaptive and maladaptive motivation [5]. Learners with a growth mindset are hypothesized to be more intrinsically motivated, while those with a fixed mindset are thought to lean toward extrinsic motivation. Unlike mindsets, effort beliefs, and goal-setting behaviours, these motivation types were not formally incorporated within the self-theories framework. However, self-determination theory [4], with its emphasis on growth orientation, offers a fitting approach to bridge this gap. The concept of academic motivation within self-determination theory [32, 33] distinguishes between adaptive, autonomous motivation and maladaptive, controlled motivation. This framework was therefore chosen to operationalize growth orientation in learning motivation.

### 1.4. Model Complexity

In the standard bifactor-ESEM model, both the global factor and all specific factors serve as exogenous variables in prediction equations. In terms of variables, this standard B-ESEM model has a complexity comparable to the standard SEM model, where all specific factors act as predictors [34]. However, the introduction of the global factor slightly increases the complexity of the B-ESEM model in terms of the total number of predictors. Despite this, the B-ESEM model achieves a more parsimonious parameterization because all factors are orthogonal by design, unlike in standard SEM, where factors are collinear. A third model type, however, is by far the simplest in terms of the number of factors and parameters: a structural equation model that explains learning motivation facets solely through growth orientation, represented by the global factor, without including any specific factors.

### 1.5. Research Objectives

Two interconnected research objectives emerge in this context:

- To explore and illustrate by means of an authentic example the potential role of the growth orientation concept within theoretical frameworks of academic motivation;
- To analyse cultural diversity in academic motivation by applying the Hofstede framework of cultural value dimension scores to form culture clusters;
- To investigate how cultural diversity impacts various types of antecedent models of motivational facets, ranging from simple to complex structures, to advocate for the adoption of simpler and more stable models.

In assessing cultural diversity, we use gender differences as an intuitive benchmark for comparison. Regarding the evaluation of model complexity, three types of models are the focus:

- Simple models: Antecedent models with a single predictor variable, Growth Orientation, using the ESEM-within-CFA framework;
- Moderately complex models: Antecedent models incorporating both the global growth factor and the five specific growth factors as predictors, also analysed using the ESEM-within-CFA framework;
- Complex models: Traditional SEM-based models explaining motivational facets through antecedent variables, including task- and potential-based approach goal setting, autonomous motivation, and incremental theory or growth mindset.

## 2. Materials and Methods

### 2.1. Participants and Educational Context

This study examines first-year students at a Dutch business and economics school from the 2015/2016 to 2023/2024 academic years. The institution is known for its student-centred learning model, problem-based learning (PBL), and international focus, boasting a predominantly international student body and Triple Crown accreditation. The sample consists of 8,711 freshmen (40% female, 60% male), with 21% domestic and 79% international students. Most students enrol immediately after secondary school, with an average age of 19.20 years (SD = 0.40). Data were collected during their first course, an introductory mathematics and statistics module.

To address varying levels of mathematics and statistics proficiency, online resources complemented face-to-face education. Following a "flipped classroom" model, students prepared for tutorials individually using e-learning tools, then engaged in collaborative problem-solving in small groups.

## 2.2. Learning Analytics and Survey Design

Dispositional Learning Analytics [35, 36] enhanced student learning in the module. This approach combined trace data from digital learning platforms with self-report surveys on learning dispositions. These surveys, based on social-cognitive learning frameworks, provided personalized feedback to students and tutors while generating data for statistical projects during the module's final week. Surveys were selected to support student learning rather than to specifically serve this research.

Students completed self-report questionnaires on their learning dispositions in the module's early weeks, reflecting habits formed in high school. Surveys requiring familiarity with learning activities and graded assessments (e.g., achievement goals) were administered later. The surveys served a dual purpose: they offered personalized feedback to both students and tutors and generated data for student-led statistical projects conducted in the final week of the module. Completing the surveys was a standard assignment required of all students. Consequently, data were complete for all participants except those who withdrew from the module, whose data were excluded from the study.

The university's review board approved the use of student data for research, and students provided informed consent.

## 2.3. Materials

All surveys, including those assessing growth orientation and other learning dispositions, used a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree, with 4 as neutral).

### 2.3.1. Growth Orientation Materials

Four instruments contributed to the construction of the growth orientation measure. Each instrument was administered in full; however, only selected constructs were used as components of the growth orientation framework. In line with previous research on growth orientation [8–12], only constructs reflecting a growth mindset—such as incremental belief, positive effort belief, and autonomous motivation—were included, while opposing constructs (e.g., entity belief, negative effort belief, and controlled motivation) were excluded. Scale scores were computed from item responses and subsequently used in the latent profile analyses. To distinguish theoretical concepts from measured constructs, we use formatting conventions: names of scales and estimated latent factors are written in italics with capital letters (e.g., *Growth Orientation*), while theoretical concepts appear in plain text without capitalization (e.g., growth orientation). Item statements are provided in the **Supplementary Materials**.

**Achievement Goals**. The extended Achievement Goal Questionnaire (AGQ) is based on the 3x2 achievement goal model [29], which includes six goal constructs defined by three types of goals—task, self, and other—and two motivational valences: approach and avoidance. The AGQ was expanded to distinguish between two sub-dimensions within the self-based (intrapersonal) goals: past and potential [24]. In this study, both aspects of the self-dimension were included, resulting in eight constructs: *Task-approach* (*TAP*), *Task-avoidance* (*TAV*), two interpersonal goals—*Other-approach* (*OAP*) and *Other-avoidance* (*OAV*)—and four intrapersonal goals: *Self-approach* (*SAP*), *Self-avoidance* (*SAV*), *Potential-approach* (*PAP*), and *Potential-avoidance* (*PAV*). Following [10], we included the approach dimension of task-based goals as growth orientation construct, along with the approach dimension of potential-based goals.

**Mindsets** or **Implicit Theories of Intelligence** were measured using a two-dimensional approach, assessing both fixed mindset / entity theory and growth mindset /incremental theory of intelligence, following the method used by Martin [37]. Dweck's [5] Theories of Intelligence Scale – Self Form for Adults was used, which includes four items reflecting Entity Theory and four items reflecting Incremental Theory served that role. The *Entity Theory* items were included in the estimation of growth orientation.

**Effort Beliefs** were evaluated using two sources: ref. [5] and [31]. Ref. [5] presents various statements where effort is viewed either as a sign of low ability or as a means to develop and improve ability. Additionally, effort belief items from [31] were included, with five Positive Effort belief items and five Negative Effort belief items (see also [26, 38]). The *Positive*

*Effort* belief items were included in the estimation of growth orientation.

**Autonomous Motivation** was measured using the Academic Motivation Scale (AMS,[33]). The AMS includes seven subscales: three intrinsic motivation subscales and one identified motivation subscale, representing autonomous motivation, and two subscales—introjected and external motivation—representing controlled motivation. The A-motivation subscale represents the absence of motivation. *Autonomous Motivation* was incorporated into the growth orientation construct. For Autonomous motivation, the three AMS subscales for intrinsic motivation and the identified items were applied as indicators.

### 2.3.2. Other Learning Disposition Materials Measuring Facets of Academic Motivation

**Achievement Goals with Self-validation and Normative Focus**. A framework closely related to the mindset theory of learning, which builds on implicit intelligence theories and beliefs about effort, is the operationalization of achievement goals as outlined in the Grant and Dweck[39] instrument. This instrument is notable for not including an avoidance dimension, focusing solely on approach-based motives. It contrasts a self-validation dimension with a normative dimension. The full instrument differentiates between two types of learning goals—*Challenge-Mastery* (*CMG*) and *Learning* (*LG*)—and four types of performance goals. Among the performance goals, two are appearance-based: *Outcome* (*OG*) and *Ability Goals* (*AG*), while the other two are normative in nature: *Normative Outcome* (*NOG*) and *Normative Ability Goal* (*NAG*).

**The Motivation and Engagement Scale**[40, 41], grounded in Martin's[42] Motivation and Engagement Wheel framework, classifies learning cognitions and behaviours into adaptive and maladaptive categories across cognitive and behavioural domains. Adaptive cognitive factors include *Self-Belief* (*SB*), *Value of School* (*VS*), and *Learning Focus* (*LF*), while adaptive behavioural factors involve *Planning* (*Pl*), *Study Management* (*SM*), and *Persistence* (*Ps*). Maladaptive cognitive factors, such as *Anxiety* (*An*), *Failure Avoidance* (*FA*), and *Uncertain Control* (*UC*), may sometimes serve as activating cognitions, while maladaptive behaviours, such as *Self-Handicapping* (SH) and Disengagement (*Ds*), consistently hinder engagement.

**Hofstede's Six Cultural Value Dimensions** provide country-specific scores for the following aspects: *Power Distance* (*PDI*), *Individualism versus Collectivism* (*IDV*), *Masculinity versus Femininity* (*MAS*), *Uncertainty Avoidance* (*UAC*), *Long-term versus Short-term Orientation* (*TOWVS*), and *Indulgence versus Restraint* (*IVR*). These scores are not directly measured in this study but are sourced from[17] (see also http://www.geert-hofstede.com/). Individual students were assigned country scores based on the location of their secondary education. Students who graduated in countries without available cultural value dimension scores were excluded from cultural profiling.

## 2.4. Statistical Analyses

The statistical analyses were conducted in four phases. In the first phase, following[10], a bifactor exploratory factor model was estimated for growth orientation as the global factor. Specific factors included the approach dimensions of task-based and potential-based goal setting, the incremental theory of intelligence, positive effort beliefs, and autonomous motivation. To ensure balanced contributions from these five factors to the global factor, indicators for positive effort beliefs and autonomous motivation were parcelled, resulting in three to four indicators per specific factor.

In the bifactor model, items simultaneously loaded on both the global (G) factor and their respective specific (S) factors, with no cross-loadings between S factors. The G factor and S factors were specified as orthogonal, ensuring interpretability consistent with bifactor assumptions. The G factor captured shared variance across all items, while S factors accounted for variance unique to their constructs[6, 7]. The B-ESEM model was estimated in ICM specification, that is without allowing correlated uniqueness between any pair of items[6, 7].

ESEM models were specified using oblique target rotation, allowing item loadings on their designated factors to be freely estimated, while cross-loadings were "targeted" to approach zero[43]. All analyses were performed using Mplus 8.10 with the maximum likelihood (ML) estimator.

In the second phase, mixture modelling was applied to the cultural index values to assign students to latent classes. Since students from the same country of secondary education share identical cultural index scores, mixture modelling grouped countries into classes based on the similarity of their cultural scores. The determination of the optimal number of latent classes was guided by substantive considerations, as statistical criteria such as fit and information indices often suggest increasing the number of classes indefinitely. What is a common outcome of mixture modelling: "... *most of the statistical fit criteria indicate better fit as more profiles are added to the model, which is not uncommon for LPAs*" ([44], p. 858).

In the third phase, following Morin and Asparouhov [45], we utilized the unstandardized loadings and cross-loadings from the bifactor ESEM model to estimate ESEM-within-CFA models [6, 7]. This approach was employed to examine the relationships between the global and specific growth orientation constructs and various aspects of learning motivation, including goal setting and motivation & engagement. To achieve this, the B-ESEM model was extended into a SEM framework, introducing structural paths to generate predictive equations for all motivational constructs. These equations included both the global growth orientation and all specific growth components as predictors, enabling the separation of their respective predictive effects. Given the complexity of the ESEM-within-CFA model, the analysis was conducted using partial models. This involved dividing the motivation & engagement constructs into adaptive and maladaptive categories and the goal-setting constructs into normative behaviours and other types of behaviours.

In the fourth and final phase, the SEM models developed in the third phase were re-estimated using the six cluster profiles as a grouping variable. Additionally, a second re-estimation was performed based on gender grouping to provide a benchmark for evaluating the magnitude of cluster differences in goal-setting behaviour, as well as adaptive and maladaptive motivation and engagement. To examine the impact of model complexity on measured cultural diversity, we compared three levels of model complexity: (1) simple models with growth orientation as the sole latent explanatory factor, (2) the full bifactor model with both global and specific growth factors as a moderately complex model, and (3) a complex structural equation model with the same exogenous latent constructs as the B-ESEM model. While the structural equation model has no more variables than the growth orientation-only model, its complexity increases due to the collinearity of exogenous latent factors, unlike the B-ESEM model, which produces orthogonal global and specific factors. This higher parameter complexity led to convergence issues during the estimation of some structural equation models. Removing positive effort views as an exogenous latent factor resolved these issues and had the added benefit of aligning the models more closely with existing research, as very few studies on academic motivation include effort views.

Cultural diversity can be formally assessed using chi-square tests; however, there are two reasons not to do so in this study. First, given the large sample sizes, nearly every beta coefficient in one cultural class is statistically significantly different from the corresponding beta in another class. As a result, the focus shifts from purely statistical significance to considering both statistical and practical significance. While statistical significance has clear, objective standards, practical significance does not, making it harder to interpret. Second, with the number of cultural classes, alternative models, and predictor variables in play, formal significance testing would require an overwhelming number of tests. Instead, we take a more intuitive approach to investigating cultural diversity, such as comparing the variation explained by cultural class differences to the variation explained by gender differences.

# 3. Results

## 3.1. Descriptive Statistics and Bifactor ESEM Model

Descriptive statistics are provided in **Table 1**; correlations confine themselves to the five variables that compose our extended growth orientation constructs, other correlations are described in the **Statistical Supplementary Materials**. Given the neutral anchor of 4 for the Likert 1...7 scale, all means of adaptive dispositions are beyond the neutral score, except for the *Normative Ability Goal* (*NAG*). All maladaptive dispositions find means below the neutral score, except for *Anxiety* (*An*). Reliabilities range from acceptable to good, except for a weaker score for the *Effort Positive* (*EP*) scale.

The hypothesized measurement model in the B-ESEM exhibited a good fit to the data ($\chi^2(39) = 154$, $p < 0.001$; CFI = 0.998; RMSEA = 0.018). With the exception of item IT4, all items showed strong standardized factor loadings with the global *Growth Orientation* construct (**Table 2**). For the specific growth constructs, items generally demonstrated high loadings on their intended constructs (highlighted in grey in **Table 2**), while cross-loadings with other specific growth constructs were relatively weak.

**Table 1.** Descriptive statistics.

| | M | Sd | ω | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|---|---|
| 1. *TAP: Task Approach* | 6.291 | 0.814 | 0.843 | 1 | | | | |
| 2. *PAP: Potential Approach* | 6.439 | 0.755 | 0.852 | 0.631 | 1 | | | |
| 3. *IT: Incremental Theory* | 4.735 | 1.124 | 0.864 | 0.065 | 0.118 | 1 | | |
| 4. *EP: Effort Positive* | 5.319 | 0.689 | 0.639 | 0.173 | 0.228 | 0.291 | 1 | |
| 5. *Aut: Autonomous Motiv.* | 5.308 | 0.743 | 0.856 | 0.177 | 0.220 | 0.175 | 0.375 | 1 |
| 6. *OG: Outcome Goal* | 6.038 | 0.810 | 0.840 | 0.300 | 0.315 | 0.164 | 0.424 | 0.353 |
| 7. *AG: Ability Goal* | 4.649 | 1.132 | 0.719 | 0.167 | 0.137 | 0.125 | 0.243 | 0.297 |
| 8. *NOG: Norm Outcome G.* | 4.164 | 1.220 | 0.756 | 0.125 | 0.076 | 0.041 | 0.149 | 0.227 |
| 9. *NAG: Norm. Ability G.* | 3.049 | 1.371 | 0.905 | 0.038 | −0.028 | −0.036 | −0.013 | 0.088 |
| 10. *LG: Learning Goal* | 5.671 | 0.825 | 0.774 | 0.215 | 0.274 | 0.241 | 0.525 | 0.423 |
| 11. *CMG: Chall.Mast.G.* | 4.827 | 0.999 | 0.767 | 0.108 | 0.155 | 0.203 | 0.438 | 0.361 |
| 12. *SB: Self−Belief* | 5.926 | 0.727 | 0.780 | 0.214 | 0.221 | 0.131 | 0.301 | 0.254 |
| 13. *VS: Value School* | 5.888 | 0.671 | 0.784 | 0.201 | 0.238 | 0.143 | 0.330 | 0.403 |
| 14. *LF: Learning Focus* | 6.204 | 0.666 | 0.788 | 0.232 | 0.289 | 0.129 | 0.308 | 0.366 |
| 15. *Pl: Planning* | 4.813 | 1.058 | 0.665 | 0.129 | 0.205 | 0.155 | 0.280 | 0.296 |
| 16. *SM: Study Managem.* | 5.611 | 0.906 | 0.757 | 0.165 | 0.235 | 0.161 | 0.281 | 0.283 |
| 17. *Ps: Persistence* | 5.473 | 0.815 | 0.783 | 0.212 | 0.272 | 0.132 | 0.373 | 0.328 |
| 18. *An: Anxiety* | 4.632 | 1.241 | 0.739 | 0.018 | 0.056 | 0.015 | −0.016 | 0.059 |
| 19. *FA: Failure Avoidance* | 2.589 | 1.254 | 0.825 | −0.058 | −0.108 | −0.043 | −0.095 | −0.045 |
| 20. *UC: Uncertain Control* | 3.474 | 1.151 | 0.807 | −0.085 | −0.078 | −0.058 | −0.144 | −0.067 |
| 21. *SH: Self−Handicapping* | 2.308 | 1.078 | 0.845 | −0.176 | −0.231 | −0.085 | −0.208 | −0.167 |
| 22. *Ds: Disengagement* | 1.795 | 0.797 | 0.828 | −0.186 | −0.241 | −0.101 | −0.245 | −0.249 |

Note: $p < 0.01$ for all correlations larger than .2 in absolute size.

**Table 2.** Standardized Factor Loadings of the B-ESEM.

| Items | *G: Growth Orientation* | *TAP: Task Approach Goal* | *PAP: Potential Approach* | *IT: Incremental Theory* | *EP: Effort Positive* | *Aut: Autonomous Motivation* |
|---|---|---|---|---|---|---|
| *TAP1* | 0.603*** | 0.466*** | 0.043* | −0.056*** | −0.055*** | −0.044*** |
| *TAP2* | 0.601*** | 0.503*** | 0.026* | −0.056*** | −0.016* | −0.019** |
| *TAP3* | 0.686*** | 0.544*** | 0.065*** | −0.062*** | −0.041*** | −0.047*** |
| *PAP1* | 0.667*** | 0.095*** | 0.373*** | −0.027*** | −0.036*** | −0.023** |
| *PAP2* | 0.754*** | 0.022 | 0.493*** | −0.024*** | −0.049*** | −0.037*** |
| *PAP3* | 0.677*** | 0.052*** | 0.427*** | −0.007 | 0.001 | −0.013 |
| *IT1* | 0.253*** | −0.124*** | −0.103*** | 0.709*** | 0.039*** | −0.005 |
| *IT2* | 0.202*** | −0.074** | −0.050 | 0.782*** | 0.027* | 0.015 |
| *IT3* | 0.253*** | −0.054* | −0.070** | 0.663*** | 0.077*** | 0.019 |
| *IT4* | 0.036 | 0.119*** | 0.170*** | 0.790*** | 0.106*** | 0.087*** |
| *EP1* | 0.281*** | −0.010 | 0.065** | 0.182*** | 0.491*** | 0.224*** |
| *EP2* | 0.270*** | −0.031* | −0.052** | 0.078*** | 0.361*** | 0.048*** |
| *EP3* | 0.354*** | −0.062*** | −0.078*** | 0.101*** | 0.650*** | 0.103*** |
| *Aut1* | 0.350*** | −0.021* | 0.007 | 0.042*** | 0.113*** | 0.724*** |
| *Aut2* | 0.371*** | −0.021** | −0.022** | 0.031*** | 0.083*** | 0.742*** |
| *Aut3* | 0.322*** | −0.035*** | −0.029** | 0.050*** | 0.070*** | 0.725*** |

Note: : *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$; greyed are global and targeted specific loadings.

The strongest components of the *Growth Orientation* construct were associated with items from the two goal-setting scales—*Task Approach Goal* and *Potential Approach Goal*. For these items, the factor loadings on the global construct exceeded those on the specific constructs. *Autonomous Motivation* items followed in importance, albeit at a distance.

Items from the *Incremental Theory* and *Effort Positive* belief constructs played a smaller role. Despite their lower reliability, the Effort Positive items were retained for substantive reasons, acknowledging their consistent but limited influence on the overall *Growth Orientation* construct.

## 3.2. Culture Based Latent Classes

As part of the exploratory analysis, latent class analyses were conducted for various numbers of classes. The goal was to determine the optimal number of latent classes based on both substantive considerations—focusing on the interpretability of the latent classes—and statistical criteria, including fit and information indices. However, the statistical criteria did not provide a definitive answer. As is often the case in latent class analysis, the statistical criteria continued to improve with an increasing number of classes, without identifying a clear optimum. Substantive considerations indicated that a six-class solution was most appropriate, with three relative large and another three smaller classes. As shown in **Figure 1**, the six cultural profiles exhibit distinct variations in cultural value dimensions. Adding more than six latent classes would result in splitting the smallest class into even smaller subclasses, which could jeopardize subsequent phases of statistical analysis.

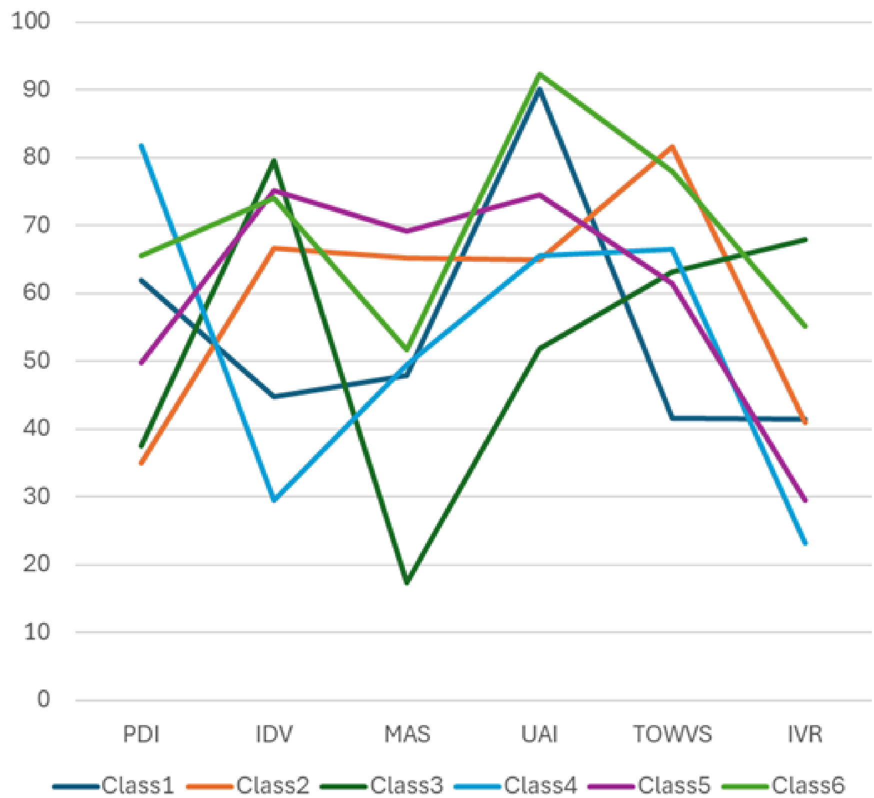


**Figure 1.** Cultural Value Dimension Scores for the 6-Latent Class Solution.

Note: *Power Distance* (*PDI*), *Individualism versus Collectivism* (*IDV*), *Masculinity versus Femininity* (*MAS*), *Uncertainty Avoidance* (*UAC*), *Long-term versus Short-term Orientation* (*TOWVS*), and *Indulgence versus Restraint* (*IVR*).

Class 1, a small group with 518 students, is characterized by a combination of collectivism, uncertainty avoidance, and short-term orientation. It is the most internationally diverse class, including students from Asia, South America, and various South and Eastern European countries. Class 2, the largest group with 2,980 students, consists of students from Germanic Europe, Eastern European countries bordering Germanic Europe, and the UK. This class is defined by values of low power distance, masculinity, and long-term orientation. Class 3, with 1,822 students, is geographically distinct, with participants from Scandinavia, two Baltic countries, and the Netherlands. Its core values include femininity, low power distance, individualism, low uncertainty avoidance, and high indulgence. Class 4, the smallest group with

302 students, represents countries from Southeast Asia and Eastern Europe and is marked by high power distance and collectivism. Class 5, another relatively small group, merges values of individualism and masculinity, with students primarily from Italy and Hungary. The final group, Class 6, consisting of 1,372 students, is defined by a blend of individualism and uncertainty avoidance, with students from parts of Latin Europe, including France, Belgium, and Malta.

The fact that European students make up the majority of our sample undoubtedly influences the classification outcomes. While non-European students are well-represented in Classes 1 and 4, their presence is limited in the other classes. However, this does not diminish the cultural diversity within the latent classes, given the rich variation in cultural values among European countries. Unequal class sizes are an artefact of the strong representation of European students in the sample.

Many studies on cultural diversity rely on country clustering according to GLOBE[19]. Although this clustering also draws on Hofstede's cultural value dimension scores, there are notable differences compared to the latent class solution. For example, the GLOBE cultural region "Latin Europe" includes all Southern European countries, whereas in the latent class solution, these countries are distributed across different classes: Class 1 (Spain, Portugal, Greece and Turkey), Class 5 (Italy), and Class 6 (France). Another significant distinction is that, in the latent class solution, the cultural values of the Netherlands align more closely with those of Scandinavian countries rather than Germanic countries, as suggested by GLOBE. Whereas GLOBE offers a general typology independent of specific samples, latent class analysis identifies groupings that optimally distinguish national cultures within the particular dataset—accounting for most of the observed differences in outcomes.

## 3.3. Structural Equation Models

Applying the ESEM-within-CFA methodology, separate SEM models were estimated in two versions: first with global and specific growth factors as exogeneous constructs, and facets of academic motivation as endogenous variables, and second the simplified versions of models of the same endogenous variables, but now with only one exogeneous variable: growth orientation. Prediction models demonstrate adequate fit (For the full versions of the prediction models: $\chi^2(266) = 3046$, $p < 0.001$; CFI = 0.975; RMSEA = 0.035 for predicting OG, AG, LG, & CMG; $\chi^2(142) = 2152$, $p < 0.001$; CFI=0.979; RMSEA=0.040 predicting NOG, NAG; $\chi^2(640) = 6375$, $p < 0.001$; CFI = 0.960; RMSEA = 0.032 for adaptive motivation & engagement; $\chi^2(515) = 5202$, $p < 0.001$; CFI = 0.965; RMSEA = 0.032 for maladaptive motivation & engagement. For the simplified versions of the prediction models: $\chi^2(283) = 5122$, $p < 0.001$; CFI = 0.956; RMSEA = 0.044 for predicting OG, AG, LG, & CMG; $\chi^2(147) = 2530$, $p < 0.001$; CFI = 0.975; RMSEA = 0.043 predicting NOG, NAG; $\chi^2(660) = 7703$, $p < 0.001$; CFI = 0.950; RMSEA = 0.035 for adaptive motivation & engagement; $\chi^2(520) = 5465$, $p < 0.001$; CFI = 0.963; RMSEA = 0.033 for maladaptive motivation & engagement. **Tables 3** and **4** report the standardized estimates of the beta coefficients, with full models in the left panel, and simplified models in the right panel.

The pivotal role of *Growth Orientation* is evident in its relationships with goal constructs measured by the Grant and Dweck (2003) instrument, which excludes the avoidance dimension in goal pursuit. **Table 3** presents the standardized beta coefficients from the structural equations explaining the six goal dimensions. For both appearance-related performance goals (*OG* and *AG*) and mastery goals (*LG* and *CMG*), global *Growth Orientation* clearly outperforms all specific factors in explanatory power, as evidenced by its standardized beta estimates, which exceed those of all other predictors. For example, in the structural equation predicting LG, the *Learning Goal*, a beta coefficient of 0.557 indicates that it accounts for approximately 31% of the variance in *LG*—representing more than half of the total explained variance (59.5%) in the full model. In contrast, the two normative performance goals (*NOG* and *NAG*) show a much weaker relationship with global *Growth Orientation* and the specific factors, with low levels of explained variation. With the exception of the two normative performance goals, explained variance ($R^2$) of the simplified model (right panel) compares well to the explained variance of the full model (left panel), indicating minimal loss of predictive power by restricting the prediction equation to *Growth Orientation* as single explanatory factor.

In the structural models explaining the motivation and engagement constructs from the motivation and engagement wheel framework, a similar divide emerges, now between adaptive and maladaptive facets. *Growth Orientation* serves as the primary explanatory factor for adaptive motivations (*SB*, *VS*, and *LF*) and adaptive engagements (*Pl*, *SM*, and *Ps*), with explained variation ranging from 22% to 43%. As with goal pursuit, beta coefficients for task and potential approach goals are predominantly negative, indicating that their strong presence within the goal orientation factor requires adjustment in the specific factor.

For maladaptive engagement factors (*SH* and *Ds*), the explained variation is lower but still highlights *Growth Orientation* as the main explanatory factor, with negative beta coefficients. In contrast, the maladaptive motivations (*An*, *FA*, and *UC*) show almost no explained variation, as detailed in **Table 4**. Anxiety, the maladaptive motivation with an activating nature, finds a positive beta for *Growth Orientation*, but predictive power nearly absent.

**Table 3.** Standardized Beta Estimates for Grant and Dweck [39] Goal Facets from Structural Equation Models (Full Model in Left Panel, Simplified Model in Right Panel).

| | *G: Growth Orient.* | *TAP: Task Appr* | *PAP: Potential Appr* | *IT: Increm. Theory* | *EP: Effort Posit.* | *Aut: Auton. Motiv.* | **$R^2$** | *G: Growth Orient.* | **$R^2$** |
|---|---|---|---|---|---|---|---|---|---|
| *OG* | 0.511*** | | −0.053*** | 0.058*** | 0.337*** | 0.204*** | 0.423 | 0.675*** | 0.455 |
| *AG* | 0.330*** | −0.125*** | 0.071*** | 0.091*** | | 0.242** | 0.196 | 0.399*** | 0.159 |
| *NOG* | 0.098*** | 0.140*** | | | 0.099*** | 0.200*** | 0.079 | 0.205*** | 0.042 |
| *NAG* | −0.050*** | 0.141*** | | | | 0.126*** | 0.038 | 0.003 | 0.000 |
| *LG* | 0.557*** | −0.328*** | | 0.108*** | 0.309*** | 0.263*** | 0.595 | 0.763*** | 0.583 |
| *CMG* | 0.473*** | −0.567*** | 0.122*** | 0.073*** | 0.073** | 0.236*** | 0.627 | 0.631*** | 0.398 |

Note: : *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$.

**Table 4.** Standardized Beta Estimates for Motivation & Engagement Wheel facets from Structural Equation Models (Full Model in Left Panel, Simplified Model in Right Panel).

| | *G: Growth Orient.* | *TAP: Task Appr* | *PAP: Potential Appr* | *IT: Increm. Theory* | *EP: Effort Posit.* | *Aut: Auton. Motiv.* | **$R^2$** | *G: Growth Orient.* | **$R^2$** |
|---|---|---|---|---|---|---|---|---|---|
| *SB* | 0.409*** | −0.062*** | | | 0.185*** | 0.137*** | 0.224 | 0.525*** | 0.276 |
| *VS* | 0.456*** | | −0.074*** | | 0.215*** | 0.340** | 0.376 | 0.651*** | 0.424 |
| *LF* | 0.428*** | | −0.112*** | | 0.179*** | 0.281*** | 0.307 | 0.610*** | 0.372 |
| *Pl* | 0.391*** | −0.306*** | | | | 181**** | 0.279 | 0.440*** | 0.194 |
| *SM* | 0.392*** | −0.172*** | −0.056*** | 0.035*** | 0.076*** | 0.165*** | 0.221 | 0.480*** | 0.230 |
| *Ps* | 0.522*** | −0.320*** | | −0.040*** | 0.131*** | 0.181*** | 0.426 | 0.611*** | 0.373 |
| *An* | 0.043** | | −0.090*** | | | 0.069*** | 0.015 | 0.072*** | 0.005 |
| *FA* | −0.160*** | | | | | | 0.026 | −0.160*** | 0.026 |
| *UC* | −0.172*** | | | | | −0.025* | 0.030 | −0.174*** | 0.030 |
| *SH* | −0.369*** | | | | | −0.072*** | 0.141 | −0.377*** | 0.142 |
| *Ds* | −0.404*** | | | | | −0.179*** | 0.195 | −0.419*** | 0.176 |

Note: : *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$.

## 3.4. Cultural Diversity versus Gender Diversity: First Order Differences

The initial examination of differences between culture-based latent classes and male and female students, serving as a benchmark, focuses on first-order differences—specifically, differences in mean levels across culture classes. These differences are often statistically significant due to the large sample size; however, their practical significance, as indicated by eta squared effect sizes, appears being limited. To address this, **Table 5** includes effect sizes for reference.

A general pattern emerges in which Class 3—characterized by high femininity, low power distance, individualism, low uncertainty avoidance, and high indulgence—consistently scores the lowest on all adaptive motivation facets, as well as on two maladaptive facets: *Anxiety* and *Failure Avoidance*. No clear pattern is observed for the remaining maladaptive facets. Notably, these two maladaptive facets (*Anxiety* and *Failure Avoidance*) exhibit relative high effect sizes, at 3.0% and 2.0%, respectively. Additionally, students in Class 4, from cultures characterized by high power distance and collectivism, tend to score higher on the two normative goal pursuit aspects and maladaptive motivation and engagement facets.

**Table 5.** Culture Class Level Differences, Left Panel, and Gender Differences, Right Panel.

| | Class1 | Class2 | Class3 | Class4 | Class5 | Class6 | $\eta^2$ | Male | Female | $\eta^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| *TAP* | 6.25 | 6.39 | 6.18 | 6.09 | 6.14 | 6.34 | 0.016 | 6.24 | 6.37 | 0.006 |
| *PAP* | 6.45 | 6.49 | 6.32 | 6.31 | 6.39 | 6.49 | 0.010 | 6.36 | 6.56 | 0.018 |
| *IT* | 4.69 | 4.66 | 4.75 | 4.94 | 4.68 | 4.87 | 0.006 | 4.66 | 4.84 | 0.006 |
| *EP* | 5.33 | 5.34 | 5.23 | 5.43 | 5.41 | 5.32 | 0.007 | 5.29 | 5.37 | 0.003 |
| *Aut* | 5.33 | 5.33 | 5.17 | 5.36 | 5.45 | 5.32 | 0.011 | 5.20 | 5.47 | 0.032 |
| *OG* | 6.15 | 6.10 | 5.92 | 6.04 | 6.01 | 6.05 | 0.009 | 5.93 | 6.20 | 0.028 |
| *AG* | 4.73 | 4.71 | 4.55 | 4.85 | 4.65 | 4.59 | 0.005 | 4.57 | 4.76 | 0.006 |
| *NOG* | 4.26 | 4.35 | 4.01 | 4.48 | 4.05 | 4.00 | 0.020 | 4.15 | 4.18 | 0.000 |
| *NAG* | 3.10 | 3.17 | 2.89 | 3.45 | 3.02 | 2.92 | 0.012 | 3.13 | 2.93 | 0.005 |
| *LG* | 5.71 | 5.75 | 5.52 | 5.81 | 5.78 | 5.64 | 0.015 | 5.61 | 5.76 | 0.008 |
| *CMG* | 4.93 | 4.80 | 4.70 | 4.94 | 5.06 | 4.90 | 0.010 | 4.85 | 4.79 | 0.001 |
| *SB* | 6.06 | 5.92 | 5.88 | 5.92 | 5.98 | 5.87 | 0.005 | 5.95 | 5.89 | 0.002 |
| *VS* | 5.95 | 5.87 | 5.78 | 5.83 | 6.09 | 5.89 | 0.013 | 5.85 | 5.95 | 0.006 |
| *LF* | 6.37 | 6.19 | 6.02 | 6.16 | 6.38 | 6.22 | 0.025 | 6.11 | 6.34 | 0.028 |
| *Pl* | 4.91 | 4.87 | 4.67 | 4.97 | 5.04 | 4.71 | 0.012 | 4.64 | 5.08 | 0.042 |
| *SM* | 5.69 | 5.66 | 5.41 | 5.68 | 5.83 | 5.62 | 0.018 | 5.47 | 5.82 | 0.037 |
| *Ps* | 5.59 | 5.50 | 5.27 | 5.56 | 5.61 | 5.46 | 0.019 | 5.39 | 5.59 | 0.014 |
| *An* | 4.89 | 4.62 | 4.30 | 4.88 | 4.70 | 4.89 | 0.030 | 4.32 | 5.09 | 0.092 |
| *FA* | 2.66 | 2.55 | 2.41 | 2.96 | 2.53 | 2.90 | 0.020 | 2.52 | 2.69 | 0.005 |
| *UC* | 3.41 | 3.37 | 3.45 | 3.57 | 3.49 | 3.75 | 0.014 | 3.37 | 3.63 | 0.012 |
| *SH* | 2.48 | 2.19 | 2.37 | 2.63 | 2.23 | 2.50 | 0.016 | 2.36 | 2.22 | 0.004 |
| *Ds* | 1.81 | 1.68 | 1.87 | 2.04 | 1.76 | 1.96 | 0.023 | 1.83 | 1.74 | 0.004 |

However, cultural differences are overshadowed by gender differences. Female students consistently score higher on all specific factors contributing to growth orientation, as well as growth orientation itself. They also outperform male students in goal pursuit, except in normative performance goals. Furthermore, females show higher levels of adaptive motivation and engagement facets but score lower in a critical area: *Self-Belief*. This lower self-belief is associated with higher scores on maladaptive motivations such as *Anxiety*, *Failure Avoidance*, and *Uncertain Control*. However, these do not translate into higher maladaptive engagement scores, which are instead higher among male students. Although gender effects exhibit modest effect sizes, they typically surpass the size of cultural differences, explaining up to 9.2% of variation in *Anxiety*.

## 3.5. Structural Equation Models for Culture-Based Classes

While mean levels across motivational facets within culture-based latent classes show minimal variation, our primary focus lies in examining class disparities within structural equations that explain motivation through its antecedents. This section delves into predictive structural equation models for specific academic motivations, thereby distinguishing three types of prediction models: models predicting outcomes using global and specific factors of growth orientation; models relying solely on the global growth orientation factor; and models employing four distinct factors from the growth orientation framework: *Autonomous Motivation*, *Task-based* and *Potential-based Approach* goal setting, and *Incremental Theory* (growth mindset). The reviewed motivational construct is the *Learning Goal (LG)*. **Table 6** provides the estimation outcomes.

The pivotal role of global *Growth Orientation* in explaining the *Learning Goal* is evident in both upper panels of **Table 6**. The beta estimates for the global construct consistently surpass those of the specific constructs. In the right panel, it is clear that excluding the specific factors as predictors has little effect on the explained variation, indicating that global *Growth Orientation* accounts for most of it. A comparison with the lower panel reveals that the G-only model explains more variation than the full path model in all classes. Regarding cultural class differences in that path model, it is notable that in class 1, *Task-based Goal* setting provides strong predictive power, whereas in other classes, *Potential-based Goal* setting together with *Autonomous Motivation* take precedence. Lastly variation in explained variation over classes is larger for the path model, than in the two versions of growth orientation models.

**Table 7** provides the estimation outcomes for the *Learning Focus* adaptive motivational construct.

**Table 6.** Antecedent Structural Relationships for *Learning Goal* (*LG*): Full Growth Orientation Model Upper Left, Simplified Growth Orientation Model Upper Right, Path Model Lower Panel.

| | ***G: Growth Orient.*** | ***TAP: Task Appr*** | ***PAP: Potential Appr*** | ***IT: Increm. Theory*** | ***EP: Effort Posit.*** | ***Aut: Auton. Motiv.*** | **R²** | ***G: Growth Orient.*** | **R²** |
|---|---|---|---|---|---|---|---|---|---|
| Class1 | 0.515*** | −0.321*** | | 0.081 | 0.384*** | 0.217*** | 0.569 | 0.715*** | 0.511 |
| Class2 | 0.535*** | −0.341*** | | 0.048* | 0.297*** | 0.281*** | 0.572 | 0.710*** | 0.505 |
| Class3 | 0.583*** | −0.479*** | | 0.078* | 0.246*** | 0.292*** | 0.722 | 0.766*** | 0.587 |
| Class4 | 0.653*** | −0.256** | | 0.175** | 0.240** | 0.151*** | 0.603 | 0.781*** | 0.610 |
| Class5 | 0.618*** | −0.375*** | | −0.011 | 0.435*** | 0.211*** | 0.756 | 0.809*** | 0.654 |
| Class6 | 0.526*** | −0.457*** | | 0.150*** | 0.289*** | 0.229*** | 0.645 | 0.719*** | 0.517 |
| Class1 | | 0.203*** | −0.020 | 0.259*** | | 0.340*** | 0.309 | | |
| Class2 | | 0.067 | 0.130*** | 0.132*** | | 0.429*** | 0.307 | | |
| Class3 | | −0.018 | 0.258*** | 0.167*** | | 0.435*** | 0.404 | | |
| Class4 | | 0.102 | 0.322*** | 0.296*** | | 0.285*** | 0.507 | | |
| Class5 | | 0.169* | 0.178* | 0.211* | | 0.345*** | 0.320 | | |
| Class6 | | −0.065 | 0.224*** | 0.254*** | | 0.380*** | 0.341 | | |

Note: : *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$.

**Table 7.** Antecedent Structural Relationships for *Learning Focus* (*LF*): Full Growth Orientation Model Upper Left, Simplified Growth Orientation Model Upper Right, Path Model Lower Panel.

| | ***G: Growth Orient.*** | ***TAP: Task Appr*** | ***PAP: Potential Appr*** | ***IT: Increm. Theory*** | ***EP: Effort Posit.*** | ***Aut: Auton. Motiv.*** | **R²** | ***G: Growth Orient.*** | **R²** |
|---|---|---|---|---|---|---|---|---|---|
| Class1 | 0.524*** | | −0.071 | 0.042 | 0.021 | 0.144** | 0.302 | 0.547*** | 0.300 |
| Class2 | 0.513** | | 0.050 | −0.010 | 0.145*** | 0.245*** | 0.347 | 0.602*** | 0.362 |
| Class3 | 0.493*** | | 0.013 | 0.036 | 0.212*** | 0.258*** | 0.356 | 0.591*** | 0.350 |
| Class4 | 0.541*** | | 0.056 | −0.011 | 0.171** | 0.254*** | 0.390 | 0.622*** | 0.387 |
| Class5 | 0.467*** | | 0.164* | −0.031 | 0.263*** | 0.191*** | 0.352 | 0.585*** | 0.342 |
| Class6 | 0.453*** | | −0.026 | 0.103** | 0.152*** | 0.251*** | 0.302 | 0.547*** | 0.299 |
| Class1 | | 0.194*** | 0.154* | 0.116* | | 0.257*** | 0.267 | | |
| Class2 | | 0.044 | 0.266*** | 0.016 | | 0.351*** | 0.277 | | |
| Class3 | | 0.093* | 0.205*** | 0.069** | | 0.368*** | 0.310 | | |
| Class4 | | 0.214* | 0.214* | 0.034 | | 0.382*** | 0.423 | | |
| Class5 | | −0.073 | 0.451*** | −0.011 | | 0.268*** | 0.285 | | |
| Class6 | | 0.023 | 0.175*** | 0.138*** | | 0.361*** | 0.263 | | |

Note: : *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$.

In the upper panel, the *G* construct once again dominates the structural prediction relationships, with beta values on the left surpassing all others and $R^2$ values on the right comparable in magnitude to those of the full bifactor model. In contrast, the lower panel shows greater variability in explained variation across classes, and *Autonomous Motivation* does not serve as the primary predictor in every class.

**Table 8** provides the estimation outcomes for the *Valuing School* adaptive motivational construct.

Once more, *Growth Orientation*, *Autonomous Motivation*, and *Positive Effort* beliefs (in four of the classes), in that sequence, account for 31% to 56% of the variation in *Valuing School*. The second panel reaffirms the predictive strength of the *G* construct, while the lower panel highlights *Autonomous Motivation* as the primary predictor in the path model, with the roles of the other predictors varying across classes.

**Table 9** provides the estimation outcomes for the *Persistence* adaptive engagement construct.

**Table 8.** Antecedent Structural Relationships for *Valuing School* (*VS*): Full Growth Orientation Model Upper Left, Simplified Growth Orientation Model Upper Right, Path Model Lower Panel.

| | *G: Growth Orient.* | *TAP: Task Appr* | *PAP: Potential Appr* | *IT: Increm. Theory* | *EP: Effort Posit.* | *Aut: Auton. Motiv.* | $R^2$ | *G: Growth Orient.* | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| Class1 | 0.590*** | −0.142 | −0.275* | | 0.120 | 0.213*** | 0.504 | 0.548*** | 0.300 |
| Class2 | 0.517*** | −0.074 | 0.038 | | 0.190*** | 0.343*** | 0.428 | 0.627*** | 0.393 |
| Class3 | 0.632*** | −0.157 | −0.100 | | 0.183*** | 0.282*** | 0.547 | 0.651*** | 0.424 |
| Class4 | 0.420*** | 0.237 | 0.114 | | 0.292*** | 0.361*** | 0.461 | 0.641*** | 0.410 |
| Class5 | 0.308*** | 0.036 | 0.231 | | 0.276*** | 0.287*** | 0.308 | 0.478*** | 0.228 |
| Class6 | 0.604*** | −0.247* | −0.211* | | 0.093 | 0.287*** | 0.562 | 0.579*** | 0.336 |
| Class1 | | 0.258*** | −0.020 | 0.135** | | 0.369*** | 0.298 | | |
| Class2 | | 0.033 | 0.229*** | 0.022 | | 0.454*** | 0.342 | | |
| Class3 | | 0.120** | 0.200*** | 0.081** | | 0.428*** | 0.393 | | |
| Class4 | | 0.344*** | 0.031 | 0.010 | | 0.468*** | 0.456 | | |
| Class5 | | −0.041 | 0.307*** | −0.037 | | 0.323*** | 0.223 | | |
| Class6 | | 0.076 | 0.117* | 0.097** | | 0.451*** | 0.323 | | |

Note: : *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$.

**Table 9.** Antecedent Structural Relationships for *Persistence* (*Ps*): Full Growth Orientation Model Upper Left, Simplified Growth Orientation Model Upper Right, Path Model Lower Panel.

| | *G: Growth Orient.* | *TAP: Task Appr* | *PAP: Potential Appr* | *IT: Increm. Theory* | *EP: Effort Posit.* | *Aut: Auton. Motiv.* | $R^2$ | *G: Growth Orient.* | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| Class1 | 0.226*** | 0.359*** | 0.518*** | 0.140** | 0.370*** | 0.263*** | 0.673 | 0.581*** | 0.338 |
| Class2 | 0.263*** | 0.181*** | 0.317*** | 0.084** | 0.447*** | 0.247*** | 0.471 | 0.535*** | 0.286 |
| Class3 | 0.274*** | 0.145* | 0.367*** | 0.169*** | 0.466*** | 0.268*** | 0.549 | 0.557*** | 0.310 |
| Class4 | 0.231*** | 0.486** | 0.410*** | 0.221** | 0.508** | 0.332*** | 0.874 | 0.608*** | 0.369 |
| Class5 | 0.311*** | 0.152 | 0.417*** | 0.018 | 0.364*** | 0.315*** | 0.525 | 0.539*** | 0.291 |
| Class6 | 0.335*** | 0.087 | 0.150* | 0.130*** | 0.379*** | 0.236*** | 0.359 | 0.530*** | 0.281 |
| Class1 | | 0.143 | 0.263*** | 0.085 | | 0.210*** | 0.271 | | |
| Class2 | | 0.038 | 0.220*** | 0.033 | | 0.282*** | 0.189 | | |
| Class3 | | −0.044 | 0.333*** | 0.099*** | | 0.285*** | 0.271 | | |
| Class4 | | 0.378*** | −0.005 | 0.167** | | 0.354*** | 0.417 | | |
| Class5 | | −0.056 | 0.418*** | −0.040* | | 0.310*** | 0.294 | | |
| Class6 | | 0.051 | 0.166** | 0.126*** | | 0.308*** | 0.221 | | |

Note: : *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$.

The prediction of the engagement factor *Persistence* deviates from the patterns observed in the previous two motivational constructs, as specific factors exhibit the highest predictive power, albeit in varying combinations. This is also evident in the right panel of **Table 9** which shows a larger gap between the $R^2$ values of the simplified growth model and the full growth model. Nevertheless, the $R^2$ values in the right panel compare well to those in the third panel.

# 4. Discussion

To explore cultural diversity, we followed McInerney's [1] call for more person-centred research by using latent class analysis to group students into relatively homogenous cultural contexts. Consistent with Hofstede's dimensional theory, this latent class analysis was based on national cultural value dimension scores. The resulting classification aligned with national borders, mirroring findings from other studies that cluster cultures by nations using cultural value dimensions [19]. However, notable differences emerged between our latent class solution and the clusters proposed by the GLOBE study. For example, the Latin Europe cluster, which represents a significant portion of students in our sample, appears to be far less homogenous than the GLOBE study suggests.

To examine whether the observed cultural diversity in models explaining motivational facets depend on model complexity, we compared three models with varying levels of complexity, applying methods for growth orientation modelling. The simplest model is the "growth orientation-only model," a structural equation model that explains the latent motivational factors solely through the latent factor of growth orientation. The most complex model is the structural equation model that incorporates all latent factors introduced in the B-ESEM model to explain the motivational constructs. For both statistical and theoretical reasons, positive effort beliefs were excluded as an explanatory factor in this analysis. Positioned between these two is the B-ESEM based model, which explains the latent motivational constructs using a combination of global and specific growth orientation factors. Although this model includes two additional exogenous latent factors—global growth orientation and positive effort beliefs—compared to the structural equation model based on specific growth factors, it remains more parsimonious in terms of model parameters due to the orthogonality of all exogenous factors it introduces in estimating the B-ESEM model.

In the comparison of simple, moderately complex, and complex models, nearly all versions of the simple model align with the universalistic perspective voiced by Soenens and Vansteenkiste [3]: universal principles apply, also in the explanation of academic motivation. In our study, this universal principle is reflected in the dominant role of global growth orientation in understanding motivation. Across cultural classes, global growth orientation consistently emerges as the key explanatory factor for appearance goals, learning goals, adaptive motivations, adaptive engagement, and even maladaptive engagement. This holds true in both the simple B-ESEM-based model and the full model. While beta estimates show some variability, these differences are comparable in magnitude to gender differences. One of the most notable aspects of this outcome is that growth orientation was initially estimated using the B-ESEM methodology in the first modelling phase, prior to dividing the sample into distinct cultural subsamples. This means that the estimated construct of growth orientation is inherently universalistic, as it was derived from the full sample without incorporating culture-specific components. Thus, not only are the principles governing the relationships between growth orientation and aspects of academic motivation universally applicable, but the very nature of the growth orientation construct itself is also universalistic. It is only in the more complex models—where complexity stems from collinearity among explanatory latent factors—that differences between latent classes become apparent, that allow an interpretation of patterns of cultural diversity.

Our finding that global growth orientation plays a central role in understanding student motivation is fully consistent with prior research. In their recent work, Bostwick and co-authors conclude "*Students' broader growth orientation demonstrated stronger and more consistent associations with students' outcomes than specific growth constructs* ([10], p. 356)". This insight has two key practical implications.

First, there is a clear need to expand our theoretical frameworks to include a wider range of growth-focused constructs beyond the widely adopted mindset models. Goal-setting theory, for instance, traditionally emphasizes comparison with others or one's past performance. The integration of forward-looking constructs such as personal-best or potential-based goals represents a valuable progression. In a recent cross-national study [46], we found that forward-looking goal setting was more strongly associated with performance and adaptive learning dispositions than retrospective goal setting. Future cross-cultural research may reveal that a growth-focused orientation is a common motivational aim among students worldwide.

Second, once these broader growth constructs are incorporated, attention should turn to how they function together within an 'integrative network of growth-focused motivation' [10]. Both our findings and prior research [10] suggest that it is not individual growth constructs alone, but their synergy within a global growth orientation, that holds the greatest predictive power. With advanced statistical methods now readily available, researchers are well-equipped to explore whether including such broad, growth-focused constructs can further advance cross-cultural motivation research.

Even within such models, cultural diversity remains evident. As illustrated in our example, the explanatory power of *Growth Orientation* for *Valuing School* varies substantially across latent classes—for instance, it accounts for only 23% of the variance in Class 5, which includes students high on individualism and masculinity, compared to 42% in Class 3, composed of students with contrasting cultural profiles, such as high femininity. However, this cultural variation manifests in differing parameter estimates (i.e., beta weights) within theoretical models that retain the same structural form across all latent classes.

Rather than assuming universal laws, relative universal theories propose that the functional structure of explanatory models in education remains stable across diverse learner groups, while allowing the strength of relationships to differ. Developing such relatively universal frameworks is essential for educational practice in culturally diverse contexts, as they suggest that underlying causal mechanisms are consistent across cultures, with only the magnitude of effects varying.

## 5. Conclusions

The primary aim of this study is to highlight the potential of the growth orientation concept in designing parsimonious models that explain facets of academic motivation through their antecedents. The limited empirical studies employing this concept with bifactor exploratory structural equation modelling (B-ESEM), including the illustrative example presented here, show such promise that overlooking its utility would be a missed opportunity.

This study is based on data from a single institution which, despite its substantial international student population, remains predominantly European in character. This presents a clear limitation: while Europe encompasses considerable cultural diversity, the inclusion of institutions from other world regions would have enhanced the study's cross-cultural scope. Future research examining global growth orientation in relation to learning motivation and cultural diversity using non-European samples is therefore strongly encouraged.

In the context of examining cultural diversity in academic motivation, a key consideration is the stability of theoretical frameworks and models when applied across different groups, whether distinguished by culture or gender. When faced with cultural diversity, the instinct is often to refine frameworks by adding context-specific facets that explain academic motivation in one group but lack relevance in others. However, our illustrative example suggests that observed differences across cultural groups—and other forms of diversity, such as gender—may partly reflect the choices made during model specification and estimation, rather than inherent universalistic or particularistic qualities of the real world. When we prioritize simplicity and parsimony in model design, as exemplified by the growth orientation framework used in our study, the resulting models are more likely to exhibit robustness across diverse subsamples compared to more complex alternatives. The combined emphasis on growth-oriented constructs and an integrative framework for learning motivation offers promising tools in the pursuit of relative universal theories that explain learning motivation across culturally diverse contexts.

## Supplementary Materials

The following supporting information can be downloaded at https://journals.zycentre.com/public/CCES-146-Supplementary-Materials.rar. The Statistical Supplementary Materials presents bivariate Pearson correlations among all variables included in the structural equation models. The Supplementary Materials includes the items from the instruments used to construct the *Growth Orientation* factor.

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## Institutional Review Board Statement

Ethics approval for the study was granted by the Ethical Review Committee Maastricht University (ERCIC_044_14_07).

## Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

## Data Availability Statement

Data is available in the Dutch national data repository, DataVerse (https://dataverse.nl/).

## Conflicts of Interest

The author declares no conflict of interest.

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