Electronic Journal of Applied Statistical Analysis
EJASA, Electron. J. App. Stat. Anal.
http://siba-ese.unisalento.it/index.php/ejasa/index
e-ISSN: 2070-5948
DOI: 10.1285/i20705948v16n1p1

The use of PLS-PM to analyze progress testing results: the case of Italian degree courses in Dentistry and Dental Prosthodontics

By Grassia et al.

Published: March 15, 2023

Electronic Journal of Applied Statistical Analysis
Vol. 16, Issue 01, March 2023, 1-24
DOI: 10.1285/i20705948v16n1p1

The use of PLS-PM to analyze progress testing results: the case of Italian degree courses in Dentistry and Dental Prosthodontics

Maria Gabriella Grassia[a], Laura Antonucci[b], Rosanna Cataldo*[a], Corrado Crocetta[c], Lorenzo Lo Muzio[b], and Marina Marino[a]

[a]*Department of Social Sciences,University of Naples Federico II, Vico Monte della Pietà, 1, 80138, Naples, Italy*
[b]*Department of Clinical and Experimental Medicine, University of Foggia, Viale Pinto, 1, 71122 Foggia, Italy*
[c]*Department of Economics, University of Foggia, Largo Papa Giovanni Paolo II, 71121 Foggia, Italy*

Published: March 15, 2023

Today, Progress Testing is an established and accepted form of assessing applied knowledge in undergraduate medical curricula. This work aims to test the performance of Italian medical and dental schools and above all the growth of knowledge in the different years analyzed. At this end, we studied longitudinal data from progress testing at Italian Dental University Schools. The contribution of this work is a new perspective on the analysis of progress testing through the use of a growth curve. In particular, from a methodological point of view, we aimed to demonstrate that the PLS-PM approach can be successfully used to estimate growth curves. The results of this first analysis confirm a thesis already present in the literature, according to which a substantial amount of variation can be attributed to different rates in the growth of knowledge across medical schools.

keywords: student learning, progress testing, latent growth curve, PLS-PM.

*Corresponding author: rosanna.cataldo2@unina.it

ISSN: 2070-5948
http://siba-ese.unisalento.it/index.php/ejasa/index

1 Introduction

Many studies have focused on different topics related to students, on the relative importance of placement quality and an integrated curriculum for the development of student learning outcomes in terms of general competence, knowledge and skills (Caspersen et al., 2020), on students' experiences of their own engagement with feedback and assessment practices in higher education (Vattøy et al., 2020). In recent years, the student learning has become a topic of growing interest and importance in higher education. Researchers focused on creating tools to track student progress over time. In this study progress testing has been presented as a tool to monitor students' learning throughout their university career. In particular, this work aims to test the performance of Italian medical and dental schools and above all the growth of knowledge in the various years analyzed through the use of a growth curve.
Progress testing is a longitudinal test approach based on equivalent tests given at fixed intervals with the intention of assessing the development of functional knowledge or competence. Historically, progress testing was a new approach to assessment. Since its inception in the late 1970s at both Maastricht University and the University of Missouri-Kansas City independently, the progress testing of applied knowledge has been increasingly used in medical and health sciences programs (both undergraduate and postgraduate) across the globe. Nowadays, progress testing is used in many medical schools, in inter-institutional collaborations or for single programs (Ali et al., 2016; Freeman et al., 2010; Tio et al., 2016; Wrigley et al., 2012). It is currently used in the national progress test consortia of the United Kingdom, Italy, The Netherlands and Germany (including Austria) and in individual schools in Africa, Saudi Arabia, South East Asia, the Caribbean, Australia, New Zealand, Sweden, Finland, and the USA. The National Board of Medical Examiners in the USA also provides progress tests in various countries. The feasibility of an international approach to progress testing has recently been acknowledged and was first demonstrated by Albano et al. (1996), who compared test scores across German, Dutch, and Italian medical schools. An international consortium has been established in Canada involving faculties in Ireland, Australia, Canada, Portugal, and the West Indies. Considerable empirical evidence from medical schools, as well as from postgraduate medical studies and schools in dentistry and psychology, has shown that the longitudinal approach of progress testing provides a unique and demonstrable measurement of the growth and effectiveness of students' knowledge acquisition throughout their course of study (Van der Vleuten et al., 2018). According to Chen et al. (2015), "progress test in a medical programme is designed to assess applied medical knowledge at the level of a new graduate and are administered to all students across all years of a programme". This kind of test is intended to discourage students from preparing specifically for a test and then put aside that knowledge. The progress test should promote meaning-orientated learning and also foster long-term knowledge retention, while reducing superficial learning strategies such as rote learning (Chen et al., 2015). Frequently, a number of tests are set in each academic year, each consisting of a large number of questions pitched at graduate level functional (relevant) knowledge. Each of these tests is taken by students of multiple or all year classes. Sometime, the

results of each individual test are combined in a compensatory way to form the basis for a promotion decision at the end of the year. The test is comprehensive in that it consists of questions covering a broad domain of relevant medical knowledge, and it is organizationally founded on centralized test production, review, administration and analysis. There are various different implementations possible, and more detailed descriptions are provided in the literature (Schuwirth et al., 2012; Swanson et al., 2010).
In Italy, progress testing is now performed both in medical schools and dental schools. In medical schools, since its inception in 2006, progress testing has been increasingly used (from 50% of schools in 2006 to 94% of schools in 2019) and the number of participating students has increased from 3.300 to more than 38.000 (Tenore et al., 2016). In 2018, the test has been redesigned on the basis of formal characteristics that have partly brought it closer to the new state exam, becoming a Training Test (TT), or training in view of the future state exam (Recchia et al., 2019). The aim of this training test was to train students to pass a national state exam and therefore the questions were not extracted by drawing on large and qualified international databases but it was necessary to strictly adhere to the "core curriculum" of the degree courses in Medicine, developed by Permanent Conference of the Presidents of the Undergraduate Dentistry and Dental Prosthodontics Curriculum (Conferenza Permanente dei Presidenti di Corso di Laurea Magistrale in Odontoiatria e Protesi Dentaria) (Gallo , 2018). In March 2017, for the first time, progress testing was established for all Italian Dental Schools, on a voluntary basis, as an initiative of the Permanent Conference of the Presidents of the Undergraduate Dentistry and Dental Prosthodontics Curriculum (Crocetta et al., 2018), with a third wave in 2019. The results of each individual test do not form the basis for a promotion decision at the end of the year, but, instead, are used, principally, to assess the performance of each Italian medical/dental university. The many different descriptions of progress testing, over time and across countries, largely converge on the principle of a longitudinal repeated assessment of students' functional knowledge.
Recently, Karay and Schauber (2018) have examined the relation between the growth trajectories obtained from progress tests using a Latent Curve Modeling (LCM) approach. As Hox and Stoel (2005) wrote in their work "a broad range of statistical methods exists for the analysis of data from longitudinal designs. Each of these methods has specific features and the use of a particular method in a particular situation depends on aspects such as the type and objective of the research". The central concern of longitudinal research, however, revolves around the description of patterns of stability and change and the explanation of how and why change does or does not take place (Kessler and Greenberg, 1981). A common design for longitudinal research in the social sciences is panel or repeated measures design, in which a sample of subjects is observed at more than one point in time (Hox and Stoel, 2005). If all individuals provide measurements at the same set of occasions, we have a fixed occasions design. When the occasions are varied, we have a set of measures taken at different points in time for different individuals. Such data occur, for instance, in growth studies, where individual measurements are collected for a sample of individuals at different occasions in their development (Growth Modeling or LCM). The data collection could be at fixed occasions, but the individuals will have different ages. Growth analysis is used to obtain a description of the mean

growth in a population over a specific period of time. However, the main emphasis consists in explaining the variability between subjects in the parameters that describe their growth curves, that is, in the inter-individual differences in intra-individual change (Willett and Sayer, 1994). LCM can be implemented and estimated within a variety of frameworks including the structural equation modeling (SEM) framework (Bollen, 1989; Kaplan, 2008), the mixed-effects (multilevel, random coefficient) (Goldstein, 2011; Hox, 2002), modeling framework (Singer et al., 2003), and the Bayesian modeling framework (Zhang et al., 2007). The explicit invocation of latent variables (LVs) afforded by the SEM makes this framework the one most commonly used to implement and estimate latent growth models (Curran, 2003; Stoel et al., 2004). The SEM framework is often used to study change processes because this framework provides an opportunity to specify multiple latent variables as predictors and outcomes.

SEM techniques include two main methods: covariance-based SEM (CB-SEM), represented by LISREL (Jöreskog and Van Thillo, 1972) and variance-based SEM, with Partial Least Squares - Path Modeling (PLS-PM) or called Partial Least Squares - Structural Equation Modeling (PLS-SEM) (Henseler and Chin, 2010; Tenenhaus et al., 2005; Wold, 1975, 1982). PLS-PM can be used to implement and to estimate latent growth models. The aim of this paper is, on the one hand, to demonstrate how PLS-PM can be used in latent growth models and, on the other, to address the question of whether or not progress testing results can be used to evaluate medical schools. If between-schools differences in initial levels of performance (intercepts) and within-school rates of growth (slopes) constitute sources of information on the development of knowledge, data from tests can be legitimately used to formulate hypotheses on medical and dental schools' patterns of knowledge growth and to stress the possible relations between initial levels of performance (intercepts) and the growth of knowledge (slopes), as well as their relation to other criteria (for example, the success of the university graduates in finding employment). In order to address this question, we use LCM with PLS-PM.

This is the first study exploring undergraduate experiences of Progress testing in healthcare education and the research presents some limits principally attributed to the data available and the type of survey. This work analyzes the only cohort available for only three years and this does not allow us to make comparisons between different cohorts and understand if there are differences between the learning and knowledge of students in the various cohorts. Furthermore, the test was administered on a voluntary basis and this can lead to biased results. Aware of the limits, however, this study would like to be a kind of experiment to show that it is possible to study trajectories with growth curves and in particular by using PLS-PM.

After an introduction to latent curve modeling, our attention will be focused on the PLS-PM approach. Longitudinal data from progress testing at Italian Dental University Schools will be analyzed by using a PLS-PM LCM approach. The results will be described in detail and some concluding remarks will be given.

2 Theoretical framework

2.1 Latent Curve Modeling

LCM is an increasingly popular approach in the analysis of longitudinal data. Though the models go by many names (e.g. latent curve models, growth curve models, latent growth models, growth models and latent trajectory models), they all refer to statistical models for longitudinal data that allow each individual in the sample to have distinct over-time trajectories of change (Bollen and Curran, 2006). LCMs emerged within SEM, but a similar technique for growth analysis was developed within the Multi-Level Modeling (MLM) framework. Mathematically, these two approaches to growth analysis can be made equivalent both are instances of the general linear model (Stoel et al., 2004). As a consequence, both allow for an estimation of *intercept* and *slope* means (fixed effects) and variances (random effects). Further, if equivalent models are estimated, the parameter estimates will be identical. Nevertheless, growth analyses in SEM and MLM use different modeling frameworks. MLM uses a regression model framework (Goldstein, 2011; Hox, 2002) whereas SEM involves a LV framework. Thus, in MLM time is a variable in the dataset and an independent variable in the regression model, whereas in SEM time is represented by the factor loadings on the latent growth factors (the intercepts and slopes). The use of different frameworks results in a number of differences between the two approaches and thus the relative strengths and limitations of each. Although LCM with SEM is not always the best approach, it is the most flexible in most cases. The general growth curve model, for the repeatedly measured variable y_{ti} of an individual i at occasion t, with a time - invariant covariate (z_i) and a time-varying covariate x_{t_i} may be written as:

$$\begin{aligned} y_{ti} &= \lambda_{0t}\xi_{int_i} + \lambda_{1t}\xi_{lin_i} + \gamma_{2t}x_{t_i} + \epsilon_{ti} \\ \xi_{int_i} &= \nu_0 + \gamma_0 z_i + \zeta_{0i} \\ \xi_{lin_i} &= \nu_1 + \gamma_1 z_i + \zeta_{1i} \end{aligned} \qquad (1)$$

where λ_{1t} denotes the time of measurement and λ_{0t} a constant equal to the value of 1. In a fixed occasions design, λ_{1t} will typically be a consecutive series of integers (0,1,2,...,T) equal to all individuals, while in a varying occasions design λ_{1t} can take on different values across individuals. The individual intercept and slope of the growth curve are represented by ξ_{int_i} and ξ_{lin_i}, respectively, with expectations ν_0 and ν_1, and random departures or residuals, ζ_{0i} and ζ_{1i}, respectively. γ_{2t} represents the effect of the time-varying y_{t-1_i}; γ_0 and γ_1 are the effects of the time-invariant covariate on the initial level and linear slope. Time-specific deviations are represented by the independent and identically standard normal distributed ϵ_{ti}, with variance σ^2_ϵ. The variances of ζ_{0i} and ζ_{1i}, and their covariance are represented by:

$$\Sigma_\zeta = \begin{matrix} \sigma_0^2 \\ \sigma_1^2\sigma_2^2 \end{matrix} \qquad (2)$$

Furthermore, it is assumed that cov($\epsilon_{it}\epsilon_{it'}$)=0, cov($\epsilon_{it}\xi_{int_i}$)=0, cov($\epsilon_{it}\xi_{lin_i}$)=0. Within MLM, ξ_{int_i} and ξ_{lin_i} are the random parameters, and λ_{1t} is an observed variable representing time. In LCM-SEM ξ_{int_i} and ξ_{lin_i} are the LVs and λ_{0t} and λ_{1t} are the parameters, that is, the factor loadings. Thus, the only difference between the models is the way in which time is incorporated. In MLM time is introduced as a fixed explanatory variable, whereas in LCM-SEM it is introduced via the factor loadings. Therefore, in longitudinal MLM an additional variable is added, while in the LCM the factor loadings for the repeatedly measured variable are constrained in such a way that they represent time. The consequence of this is that with reference to the basic growth curve model, MLR (Multi-Level Relational) is essentially a univariate approach, with time points treated as observations of the same variable, whereas the LCM is essentially a multivariate approach, with each time point treated as a separate variable (Stoel et al., 2004). The model in (1) can be extended in several ways. First, let us assume that we have collected data on several occasions from individuals within classes, and that there are (systematic) differences between the classes in terms of intercepts and slopes. The model in (1) can easily account for such a "three-level" structure by adding the class-specific subscript j. The model then becomes:

$$
\begin{aligned}
y_{tij} &= \lambda_{0t}\xi_{int_{ij}} + \lambda_{1t}\xi_{lin_{ij}} + \gamma_{2t}y_{t-1_{ij}} + \epsilon_{tij} \\
\xi_{int_{ij}} &= \nu_{0j} + \gamma_0 z_i + \zeta_{0ij} \\
\xi_{lin_{ij}} &= \nu_{1j} + \gamma_1 z_i + \zeta_{1ij} \\
\nu_{0j} &= \nu_0 + \zeta_{2j} \\
\nu_{1j} &= \nu_1 + \zeta_{3j}
\end{aligned}
\tag{3}
$$

The mean intercept and slope may be different across classes. If ζ_{2j} and ζ_{3j} are constrained to zero, the model turns into (1). It is straightforward to incorporate class level covariates and additional higher levels in the hierarchy.
Secondly, the model in (1) can be easily extended to include multiple indicators of a construct at each occasion explicitly. This approach has been termed second-order growth modeling, in contrast to first-order growth modeling in relation to the observed indicators (Figure 1). If the items of each occasion are R, y_{rti} can be modeled directly, as indicators of a latent construct or factor at each measurement occasion. The model incorporating all y_{rti} explicitly, then becomes:

$$
\begin{aligned}
y_{rti} &= \alpha_r + \lambda_r\tau_{ti} + \epsilon_{ri} \\
\tau_{ti} &= \lambda_{0t}\xi_{int_i} + \lambda_{1t}\xi_{lin_i} + \gamma_{2t}y_{t-1_i} + \zeta_{ti} \\
\xi_{int_i} &= \nu_{0j} + \gamma_0 z_i + \zeta_{0ij} \\
\xi_{lin_i} &= \nu_1 + \gamma_1 z_i + \zeta_{2j}
\end{aligned}
\tag{4}
$$

where α_r and λ_r represent, respectively, the item specific intercept and factor loading of item r, and ϵ_{ri}i is a residual. τ_{ti} an individual and time-specific latent factor corresponding to y_{ti} of model (1) and ζ_{ti} a random deviation corresponding to ϵ_{ti} of model

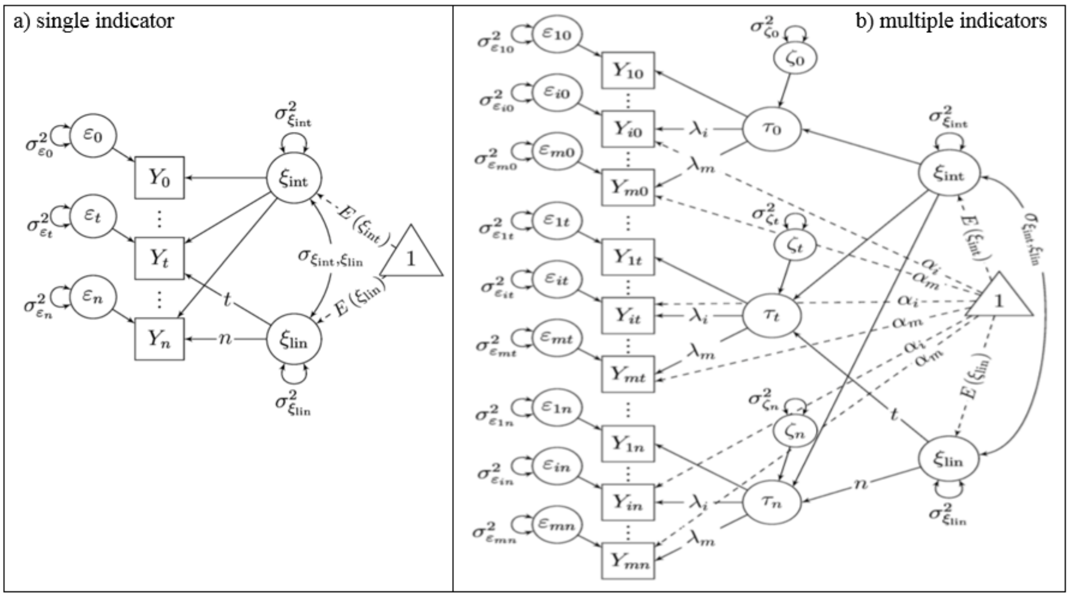


Figure 1: (a) First-order growth modeling - SEM model. (b) Second-order growth modeling - SEM model. Source: Geiser et al. (2013)

(1). The growth curve model is subsequently built on the latent factor scores τ_{ti} with λ_{1t} representing the time of measurement and λ_{1t} a constant equal to the value of 1. This model thus allows for a separation of the measurement error ϵ_{ri} and individual time-specific deviation ζ_{ti}. In model (1) these components are confounded in ϵ_{ti}.

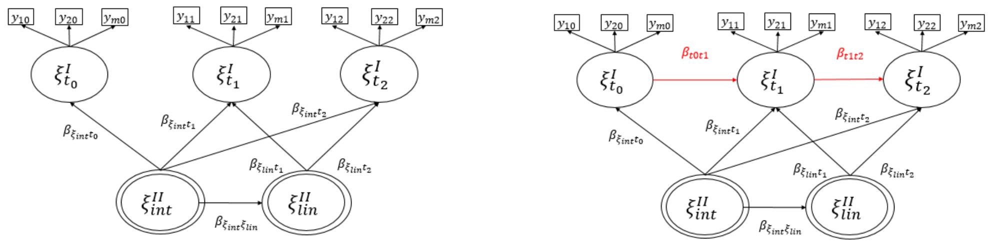
Thirdly, it is possible to estimate a non-linear model. Thus, instead of constraining λ_{1t} to, for example [0,1,2,3...T], some elements are left free to be estimated, providing information on the shape of the growth curve. For purposes of identification, at least two elements of λ_{1t} need to be fixed. The remaining values are then estimated to provide information on the shape of the curve; λ_{1t} then becomes $[0,1,\lambda_{12},\lambda_{13},...,\lambda_{1T-1}]$. Therefore, essentially, a linear model is estimated, while the non-linear interpretation comes from relating the estimated λ_{1t} to the real time frame (Meredith and Tisak, 1990; Stoel et al., 2004). The transformation of λ_{1t} to the real time frame gives the non-linear interpretation.

2.2 The PLS-PM approach/estimator to SEM

In the previous paragraph, we have analyzed LCM from the perspective of CB-SEM. Recently, Roemer (2016) has proposed using the component-based approach to SEM (PLS-PM) (Vinzi Esposito et al., 2010; Tenenhaus et al., 2005; Wold, 1982) in a longitudinal study. Both methods, CB-SEM and PLS-PM are complementary rather than competitive (Hair et al., 2017). Even though this issue is well-known (Jöreskog and Wold, 1982), many researchers still focus on comparing the differences between model estimations when using CB-SEM or PLS-PM composite models (Hair et al., 2014). As Hair et al. (2017), we believe that PLS-PM researchers should follow Rigdon (2014) suggestion and begin emancipating the method from its CB-SEM sibling (Rigdon, 2014; Sarstedt et al., 2020). For example, Fornell and Bookstein (1982), Hair et al. (2011), Hair et al. (2012), Jöreskog and Wold (1982) and Reinartz et al. (2009) provide recommendations about when to use CB-SEM and when PLS-PM. The most important reason driving the selection of either CB-SEM or PLS-PM is the research goal (structure or prediction): the primary purpose of the CB approach is to study the structure of the observables, the primary purpose of the PLS approach is to predict the indicators by means of the component expansion (Jöreskog and Wold, 1982).

Generally, the choice of using the PLS-PM is particularly useful for several reasons. This approach has as its main advantages its applicability to small sample, the ability to estimate quite complex models (with many latent and observable variables) and less restrictive requirements concerning normality and variable and error distributions (Henseler et al., 2009). Furthermore, PLS-PM approach provides the possibility of working with missing data and in the presence of multi-collinearity. Another advantage of this approach, as compared to other multivariate techniques, is that it examines simultaneous a series of dependence relationship, using a single statistical approach to test the full scope of projected relations (Hair et al., 1998). Furthermore, this approach provides researchers with much more flexibility as it enables using both formative and reflective measurement models, providing a more nuanced testing of theoretical concepts (Hair et al., 2011). It is advisable to use the PLS-PM because it is very flexible and robust and does not require distributive assumptions and lower requirements for model identification (Lauro et al., 2018; Ciavolino and Nitti, 2013; Ciavolino et al., 2022b).

In accordance with Roemer (2016), we posit that PLS path modeling is highly appropriate for an analysis of the development and change in constructs in longitudinal studies, since it offers three favorable methodological characteristics. First, constructs often need to be predicted in evolutionary models (Johnson et al., 2006; Shea and Howell, 2000). Secondly, model complexity quickly increases when development and change need to be analyzed in longitudinal studies. This is due to the larger number of constructs that are measured at different points in time and the respective effects between those constructs (Johnson et al., 2006). PLS-PM is well suited to dealing with such complex models (Fornell and Cha, 1994; Wold, 1985). Thirdly, sample sizes can become quite small in longitudinal studies (Jones et al., 2002). PLS-PM is particularly appropriate in such cases (Hair et al., 2014). Furthermore, many developments recently made in the PLS-PM algorithm may be very useful if applied to longitudinal studies, and particularly, if applied to estimate LCMs. PLS-PM is now a full-fledged variance-based estimator for SEM that can estimate linear, non-linear, recursive and non-recursive structural models (Dijkstra and Henseler, 2015a,b). Moreover, it is capable of dealing with Higher-Order Construct Models (Cataldo et al., 2017; Ciavolino et al., 2015; Rajala and Westerlund, 2010) and ordinal categorical indicators (Schuberth et al., 2008). It can incorporate sampling weights known as weighted partial least squares (Becker and Ismail, 2016), and address multicollinearity among the constructs in the structural model (Jung and Park, 2018). Finally, it can also be used for multiple group comparison (Sarstedt et al., 2011). To analyse the progress test data, we have proposed using consistent PLS-Higher-



(a) without the impact of $\xi^{I}_{t_{i-1}}$ on $\xi^{I}_{t_i}$ (b) with the impact of $\xi^{I}_{t_{i-1}}$ on $\xi^{I}_{t_i}$

Figure 2: Growth modeling - PLS-PM model three times with m indicators in each n times

Order Construct Modeling. Other developments, such as non-linear PLS-PM, will be used in our future research.

2.3 Latent Curve Models with the PLS-PM approach

In Wold (1982) original design of PLS-PM it was expected that each construct would necessarily be connected to a set of observed variables. On this basis, Lohmöller (2013) proposed a procedure to treat hierarchical constructs, the so-called hierarchical component model. This kind of model allows for a reduction of the model complexity and theoretical parsimony (Ciavolino, 2012; Ciavolino et al., 2022a). Sarstedt et al. (2019) provide in their study the guidance that scholars, marketing researchers, and practitioners need when using Higher-Order constructs in their studies. There are several main reasons for the inclusion of a Higher-Order Construct Model: Higher-Order Construct Models prove valuable if the constructs are highly correlated; the estimations of the structural model relationships may be biased as a result of collinearity issues, and a discriminant validity may not be established. In situations characterized by collinearity among constructs, a Second-Order Construct can reduce such collinearity issues and may solve discriminant validity problems. PLS path modeling allows for the conceptualization of a hierarchical model, through the use of the main approaches existing in the literature: the Repeated Indicators Approach (Lohmöller, 2013), the Two Step Approach (Rajala and Westerlund, 2010) and the Hybrid Two Step Approach (Ciavolino and Nitti, 2013), then taken up by Cataldo et al. (2017) with the name of Mixed Two Step Approach. The Repeated Indicators Approach is the most popular approach when estimating Higher-Order Constructs in PLS-PM (Wilson, 2010). The different approaches concern the determination of the Higher-Order construct, leaving the inner model unchanged. Regardless of the approach used, we propose using a Higher-Order Construct Model to estimate a LCM. An example, with three points in time, is presented in Figure 2.

The Higher-Order LV ξ^{II}_{int} describes the mean growth, and the LV ξ^{II}_{lin}.the mean slope. ξ^{II}_{int} is reflected in the construct of first order $\xi^{I}_{t_0}$, $\xi^{I}_{t_1}....\xi^{I}_{t_n}$. The construct of second order ξ^{II}_{lin} is reflected in the construct of first order $\xi^{I}_{t_1}....\xi^{I}_{t_n}$. The equations of the inner model are:

$$
\begin{aligned}
&\xi_{lin}^{II} = \beta_{0lin} + \beta_{\xi_{int}\xi_{lin}}\xi_{int}^{II} + \zeta_{lin} \\
&\xi_{t_0}^{I} = \beta_{0t_0} + \beta_{\xi_{int}t_0}\xi_{int}^{II} + \zeta_{t_0} \\
&\xi_{t_1}^{I} = \beta_{0t_1} + \beta_{\xi_{int}t_1}\xi_{int}^{II} + \beta_{\xi_{lin}t_1}\xi_{lin}^{II} + \zeta_{t_1} \\
&... \\
&\xi_{t_i}^{I} = \beta_{0t_i} + \beta_{\xi_{int}t_i}\xi_{int}^{II} + \beta_{\xi_{lin}t_i}\xi_{lin}^{II} + \zeta_{t_i} \\
&\xi_{t_n}^{I} = \beta_{0t_n} + \beta_{\xi_{int}t_n}\xi_{int}^{II} + \beta_{\xi_{lin}t_1}\xi_{lin}^{II} + \zeta_{t_n}
\end{aligned} \tag{5}
$$

where:

- $\beta_{\xi_{int}\xi_{lin}}$ is the strength and sign of the relations between construct ξ_{lin}^{II} and the predictor construct ξ_{int}^{II};
- $\beta_{\xi_{int}\xi_{lin}}$ representing the growth mean rate;
- $\beta_{\xi_{int}t_i}$ is the strength and sign of the relations between construct $\xi_{t_i}^{I}$ and the predictor construct ξ_{int}^{II};
- $\beta_{\xi_{lin}t_i}$ is the strength and sign of the relations between construct $\xi_{t_i}^{I}$ and the construct ξ_{lin}^{II}.

They indicate how both intercept and slope factors contribute to explaining each time. β_0 is just the intercept term and ζ accounts for the residuals. The intercept term β_0 of each equation should always be non-significant. If we introduce the impact of the LV at *i*-1 time ($\xi_{t_{i-1}}^{I}$) on the LV at i time ($\xi_{t_i}^{I}$), for its better prediction ($\xi_{t_0}^{I} \rightarrow \xi_{t_1}^{I}$; $\xi_{t_1}^{I} \rightarrow \xi_{t_2}^{I}$;....; $\xi_{t_{n-1}}^{I} \rightarrow \xi_{t_n}^{I}$) as in Figure 2 (b), the equations of the inner model become:

$$
\begin{aligned}
&\xi_{lin}^{II} = \beta_{0lin} + \beta_{\xi_{int}\xi_{lin}}\xi_{int}^{II} + \zeta_{lin} \\
&\xi_{t_0}^{I} = \beta_{0t_0} + \beta_{\xi_{int}t_0}\xi_{int}^{II} + \zeta_{t_0} \\
&\xi_{t_1}^{I} = \beta_{0t_1} + \beta_{\xi_{int}t_1}\xi_{int}^{II} + \beta_{\xi_{lin}t_1}\xi_{lin}^{II} + \beta_{t0t1}\xi_{t_0}^{I} + \zeta_{t_1} \\
&... \\
&\xi_{t_i}^{I} = \beta_{0t_i} + \beta_{\xi_{int}t_i}\xi_{int}^{II} + \beta_{\xi_{lin}t_i}\xi_{lin}^{II} + \beta_{t_{i-1}t_i}\xi_{t_{i-1}}^{I} + \zeta_{t_i} \\
&\xi_{t_n}^{I} = \beta_{0t_n} + \beta_{\xi_{int}t_n}\xi_{int}^{II} + \beta_{\xi_{lin}t_1}\xi_{lin}^{II} + \zeta_{t_n}
\end{aligned} \tag{6}
$$

where $\beta_{t_{i-1}t_i}$ represent the carry-over effects (Johnson et al., 2006; Duncan et al., 2013). Carry-over effects are special effects that emerge from one construct at one point in time to the same construct at a subsequent point in time (Johnson et al., 2006; Roemer, 2016). In this way, an evaluation of a construct at a subsequent point in time represents an updated version of its prior evaluation (Bolton and Drew, 1991; Oliver, 1980). A sizeable positive effect means that the individuals' estimations of the construct remain stable over time (Duncan et al., 2013). In contrast, a small effect means that there has been a substantial reshuffling of the individuals' standings on the construct

over time (Selig and Little, 2012). Finally, a sizeable negative effect means that there has been a reversal of the position of individuals on the structure over time. $\beta_{t_{i-1}t_i}$ contributes to explaining the variability at t time.
As in the CB-SEM framework, the model must be evaluated: first the measurement model and then the structural model. For the measurement model the Dillon-Goldstein's Rho, the mean of communalities and the mean redundancies must be examined. The structural model quality of the inner model must be assessed by examining the following indices: the regression weights, the coefficient of determination (R^2), the redundancy index, and the goodness-of-fit (GoF) statistics (Tenenhaus et al., 2005). If the structural model quality is well assessed, but one or more *carry-over effects* are negative, this means there are two or more subsamples, with different growth curves. In this case, we suggest splitting the sample into two or more subsamples. Subsequently, multi-group comparisons could be used to test any differences in the structural path estimates. Farther, the total effect must be analyzed. Considering the model in Figure 2(b), the construct $\xi^I_{t_0}$ can be considered as a mediator construct. This means that ξ^{II}_{lin} is related to both $\xi^I_{t_0}$ and $\xi^I_{t_1}$, and $\xi^I_{t_0}$ is related to variable $\xi^I_{t_1}$, and therefore the indirect effects of ξ^{II}_{lin} acting through variable $\xi^I_{t_0}$ on variable $\xi^I_{t_1}$ have to be analyzed. It is the same case in relation to the other LVs where a mediator construct is present. More specifically, mediating analysis determines the degree to which indirect effects (through the mediating variables) modify the assumed (hypothesized) direct paths, or relationships. According to Hair et al. (2017), the focus on mediation is on a theoretically established direct path relationship as well as on an additional theoretically relevant component mediator which indirectly provides information on the direct effect via its indirect effect.

3 Progress testing of Italian Dental Schools

3.1 Cross-sectional data

On 29th March 2017 the first Progress Test was carried out in all Italian Schools of Dental Medicine, as an initiative of the Italian Conference of the Presidents of the Undergraduate Dentistry and Dental Prosthodontics Curriculum (the "Conferenza Permanente dei Presidenti di Corso di Laurea Magistrale in Odontoiatria e Protesi Dentaria") with a third version in 2019. The percentage of Dental Medicine Schools participating was very high with, initially, only three schools (Catanzaro, Perugia and Milano Cattolica) not being involved in the initiative. The number of participating students, in each group, was also significant, ranging from 44% to 97% in the different schools. In Italy, degree course on Dentistry and Dental Prosthodontics last six years. Progress tests are administered once per year, from degree year one to six, at the end of the first annual semester (Crocetta et al., 2018). Participation is voluntary.

In total, students should take up to six progress tests within their dentistry and dental and prosthodontics training. The progress test consists of 300 interdisciplinary multiple-choice (MC) questions with a single-best-answer format. The items align with various areas: 150 items related to *basic sciences* (BS) and 150 to *clinical sciences* (CS), ten for each science. In Table 1 the detail of the questions is reported.

Table 1: Disciplines for the two areas

Basic Sciences		Clinical Sciences	
Behavioural Sciences	10	Principles of Dentistry	10
Chemistry and Biochemistry	10	Dental Materials	10
Physics	10	Laboratory Technologies	10
Biology and Genetics	10	Oral Pathology	10
Histology and Anatomy	10	Oral Surgery	10
Physiology	10	Periodontology	10
General Pathology	10	Hearing	10
Pharmacology	10	Gnathology	10
Internal Medicine	10	Orthodontics	10
Anestesiology and General Surgery	10	Conservative	10
Pathological Anatomy	10	Endodontics	10
Legal Medicine	10	Maxillofacial	10
Hygiene	10	Implantology	10
Neurology and Psychiatry	10	Pediatric Dentistry	10
Radiology	10	Oral Clinic	10

With these interdisciplinary questions, it is possible to study knowledge growth as students progress in their undergraduate study. PTs also provide comprehensive feedback to students so they can identify gaps in their knowledge base, which facilitates self-directed learning. The test scores the number of correctly answered items, without any deduction of points for "don't-know" or incorrect answers. The scores in Table 2 are the averages of the percentage of correct answers for each degree year from 2017 to 2019 for BS and CS questions (cross-sectional data).

Table 2: Averages of the percentage of correct answers in basic sciences (BS) and clinical sciences (CS)

Year of	Year group					
dental degree	BS	CS	BS	CS	BS	CS
1	39	19	36	21	43	24
2	49	27	42	24	47	30
3	59	39	52	39	56	44
4	68	51	60	52	63	64
5	69	62	61	68	62	73
6	68	63	61	70	65	76

3.2 Panel data

To study the developmental pattern across the course of study, only the test results of the 2016-2017 cohort of students have been analyzed. At the first wave, this cohort was in the first year of the dental degree, at the second wave the students were in the second year, and, finally, at the third wave in the third year. Only in 2022 will this longitudinal series of data be complete. The units are the schools of dental medicine of the Italian Universities. The times of measurement were three (t_0,t_1,t_2). The aim is to investigate how the developmental pattern across the course of study can be described adequately. Summary statistics of the correct answers for the BS and CS questions for the 2016-2017 cohort are provided in the Table 3.

Table 3: Summary statistics of the percentage of correct answers in basic sciences (BS) and clinical sciences (CS) for each wave

	BS			CS		
	t_0 2017	t_1 2018	t_2 2019	t_0 2017	t_1 2018	t_2 2019
mean	39,1	42,1	56,1	19,3	23,9	43,6
σ	15,8	16,6	10,8	5, 0	12,2	13,6

Summary statistics of the correct answers both for BS and CS questions for the 2016-2017 cohort are provided in the Table 4.

The XLSTAT software (2017) [1] was used for data processing and to estimate the PLS-PM model. Any missing data was handled by using the NIPALS algorithm (Wold, 1975). We used a SEM PLS-PM framework, assuming a continuum of growth from the first to the third academic year both for BS and CS. For each testing time, three LVs were considered: knowledge (K) at t_i, BS at t_i, and CS at t_i. Each BS at t_i, (BS_{t_i}) has 15 reflective MVs (behavioral sciences; chemistry and biochemistry; physics; biology and genetics; histology and anatomy; physiology; general pathology; pharmacology; internal medicine; anesthesiology and general surgery; pathological anatomy; legal medicine; hygiene; neurology and psychiatry and radiology). Equality applies to each CS at t_i, each having 15 reflective MVs (principles of dentistry; dental materials; laboratory technologies; oral pathology; oral surgery; periodontology; hearing; gnathology; orthodontics; conservative; endodontics; maxillofacial; implantology; pediatric dentistry and oral clinic). Conversely, no K at t_i has its own MVs, as each is composed by BS_{t_i} and CS_{t_i}). Therefore, the model is a Higher-Order PLS-PM model with reflective lower order and reflective-reflective higher order constructs (K_{t_0}; K_{t_1}; K_{t_2}), with reflective measurement model. Two models, shown in Figure 2, have been estimated with the Repeated Indicator: the first model without any relation between the LVs at time i-1

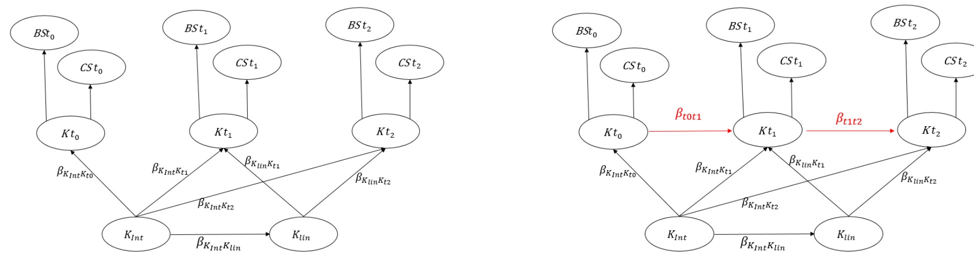
[1]XLSTAT software Copyright © 2017 Addinsoft

Table 4: 2016-2017 cohort - Summary statistics of the percentage of correct answers in each science in BS and CS for each year group

		t_0		t_1		t_2	
		2017		2018		2019	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
BS	Behavioral sciences	26,35	9,18	45,03	12,50	54,32	9,45
	Chemistry and biochemistry	66,68	11,07	54,35	8,10	65,08	9,16
	Physics	59,89	12,38	53,65	12,58	50,32	13,83
	Biology and genetics	63,38	11,62	63,82	11,26	77,00	5,71
	Histology and anatomy	58,12	14,68	67,55	11,68	58,36	12,53
	Physiology	32,46	9,83	67,86	12,72	65,37	9,50
	General pathology	49,94	10,39	41,76	16,38	65,67	8,91
	Pharmacology	31,75	13,14	35,45	15,05	55,04	19,03
	Internal medicine	41,06	10,30	25,39	15,47	52,48	9,80
	Anesthesiology and general surgery	21,29	12,34	27,39	15,42	56,45	16,15
	Pathological anatomy	33,51	13,22	21,67	14,05	55,87	14,68
	Legal medicine	39,31	11,18	32,07	15,28	43,81	16,75
	Hygiene	27,13	8,97	51,45	12,70	65,35	10,94
	Neurology and psychiatry	23,02	8,47	19,75	10,11	32,41	12,99
	Radiology	24,47	13,00	18,18	10,99	46,38	18,89
CS	Principles of dentistry	32,82	11,97	64,10	12,17	81,38	7,50
	Dental materials	28,39	10,61	22,00	13,00	38,99	10,03
	Laboratory technologies	22,04	8,91	23,84	12,32	60,39	15,68
	Oral pathology	26,59	11,81	41,85	18,34	46,88	16,96
	Oral surgery	18,85	10,58	22,07	8,68	43,46	18,57
	Periodontology	22,44	10,62	23,50	12,95	32,78	13,06
	Hearing	17,11	8,70	22,00	12,46	41,95	17,31
	Gnathology	15,16	7,11	19,19	12,02	47,83	15,23
	Orthodontics	17,00	9,80	15,20	13,30	36,79	15,44
	Conservative	17,33	10,25	19,07	13,63	45,77	18,00
	Endodontics	14,74	8,74	19,07	9,20	34,70	19,06
	Maxillofacial	17,15	9,23	15,18	8,81	21,91	11,39
	Implantology	15,82	10,43	12,45	7,52	35,63	15,97
	Pediatric dentistry	15,35	9,41	20,60	14,95	53,85	19,65
	Oral clinic	23,96	10,80	22,67	14,49	35,44	16,58

and the LVs at time *i* (Figure 2 (a)); the second model with impact without relation between LV at time *i*-1 and LV at time *i* (Figure 3 (b))

The path weighting scheme was chosen (Hair et al., 2017) for both models and they



(a) without the impact of $\xi^I_{t_{i-1}}$ on $\xi^I_{t_i}$ (b) with the impact of $\xi^I_{t_{i-1}}$ on $\xi^I_{t_i}$

Figure 3: Theoretical model

were estimated with a maximum of 1,000 iterations. For both models we used 500 replications, with a bootstrap sample equal to 1000. The overall model fit is assessed by GoF and relative GoF (Tenenhaus et al., 2005). The prediction performance of the PLS-PM is higher for the model (b) with $\xi^I_{t_{i-1}}$ that impact on $\xi^I_{t_i}$ (Table 5).

Table 5: Goodness of Fit - model (a) and model (b)

		GoF	GoF (Bootstrap)	Standard Error	Critical Ratio (CR)	LL 95% CI	UL 95% CI
Model (a)	Absolute GoF	0,57	0,58	0,02	27,85	0,53	0,62
	Relative GoF	0,85	0,84	0,02	40,79	0,81	0,89
	Outer model	0,98	0,98	0,02	46,02	0,93	1,00
	Inner model	0,87	0,86	0,01	78,49	0,85	0,89
Model (b)	Absolute GoF	0,60	0,60	0,02	26,45	0,56	0,64
	Relative GoF	0,87	0,86	0,02	38,12	0,82	0,91
	Outer model	0,98	0,98	0,02	46,72	0,93	1,00
	Inner model	0,89	0,89	0,01	75,59	0,86	0,91

The R^2 coefficients show that the endogenous LVs of model (b) are better predicted by the explanatory LVs, while the values of the communality index are appreciably higher for all blocks (the value of 0.50 indicates a sufficient degree of construct validity). Moreover, all the blocks are unidimensional, as it is possible to verify from the values of the Dillon-Goldstein's Rho reported, which are high for all blocks (Table 6).

The results for the model (b) are shown below. In order to assess the significance of the path coefficients, Table 7 reports the value and significance of the direct structural coefficients linking the constructs at different times.

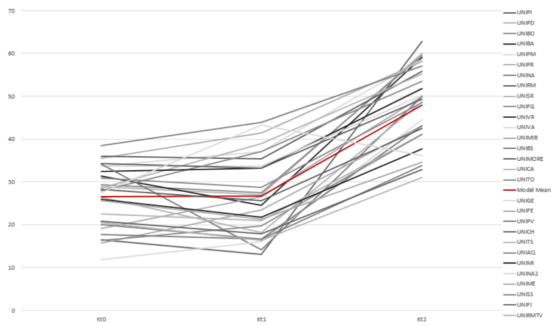
The value and significance of the structural parameters linking the different constructs in the model is considered for the evaluation of the hypothesis that there is a relation between the initial levels of performance (the intercepts) and the growth of knowledge (the slopes). The significance of all of these parameters serves to determine whether these

Table 6: Overall model quality

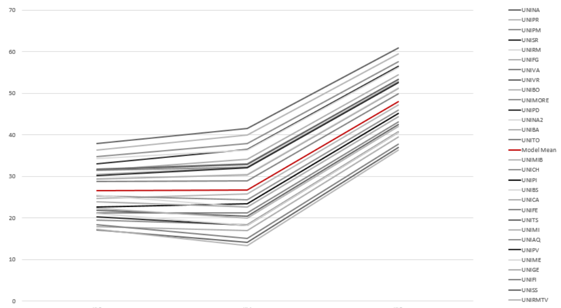
	Construct	MV	Type	R^2	R^2 adjusted	Communalities	D.G's Rho
Model (a)	K_{int}	31,76	Exog.			0,42	0,97
	K_{lin}	35,38	End.	0,94	0,94	0,41	0,96
	K_{t_0}	26,23	End.	0,76	0,76	0,45	0,96
	BS_{t_0}	35,54	End.	0,62	0,62	0,53	0,94
	CS_{t_0}	19,95	End.	0,83	0,83	0,71	0,97
	K_{t_1}	26,79	End.	0,80	0,79	0,49	0,96
	BS_{t_1}	34,38	End.	0,84	0,84	0,49	0,93
	CS_{t_1}	21,03	End.	0,91	0,91	0,63	0,96
	K_{t_2}	48,19	End.	0,61	0,60	0,47	0,94
	BS_{t_2}	55,91	End.	0,81	0,81	0,49	0,89
	CS_{t_2}	41,95	End.	0,92	0,92	0,47	0,93
Model (b)	K_{int}	31,80	Exog.			0,42	0,97
	K_{lin}	35,48	End.	0,94	0,94	0,41	0,96
	K_{t_0}	25,85	End.	0,76	0,76	0,45	0,96
	BS_{t_0}	35,44	End.	0,60	0,60	0,53	0,94
	CS_{t_0}	19,92	End.	0,85	0,85	0,71	0,97
	K_{t_1}	26,52	End.	0,93	0,93	0,49	0,96
	BS_{t_1}	34,29	End.	0,84	0,84	0,49	0,93
	CS_{t_1}	21,01	End.	0,91	0,91	0,63	0,96
	K_{t_2}	48,33	End.	1,00	1,00	0,47	0,94
	BS_{t_1}	56,03	End.	0,81	0,81	0,49	0,89
	CS_{t_2}	41,99	End.	0,92	0,92	0,47	0,93

estimates differ from zero and can be used to answer questions such as "is the amount of variation, on average, significantly different from zero?" or "is there significant variability in the rate of change of individuals?" (Berlin et al., 2014). The path coefficient between K_{lin} and K_{t_1} ($K_{lin} \rightarrow K_{t_1}$) is negative and therefore the hypothesis of a continuum of growth is not verified. For the time t_2, the path coefficient between K_{Int} and K_{t_2} (K_{lnt} $\rightarrow K_{t_2}$) is negative and not significant and therefore the hypothesis of a fixed intercept is not verified. The negative carry-over effects between K_{t_0} and K_{t_1} and K_{t_1} and K_{t_2} suggests to use an explanatory variable to explain the reversal of the unit positions from time t_1 to time t_2. In the Figure 4, a confront between observed trajectories, model-implied trajectories without effect K_{t_0}, K_{t_1}, K_{t_1}, K_{t_2} (model a) and without effect K_{t_0}, K_{t_1}, K_{t_1}, K_{t_2} (model b) is presented.

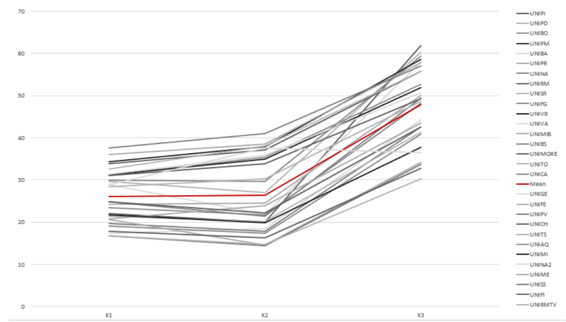
The PLS-PM Model, with the effect between the construct of time ($K_{t_0} \rightarrow K_{t_1}$ and $K_{t_1} \rightarrow K_{t_2}$) allows us to evaluate the unit performances (the best and the worst), identifying, at the same time, the intercept and the slope of the growth curve. As our aim was to investigate to what extent the between-unit variation in levels of performance



(a) Observed trajectories with Model curve



(b) Model trajectories without effect K_{t_0}, K_{t_1} and K_{t_1},K_{t_2}



(c) Model trajectories with effect K_{t_0}, K_{t_1} and K_{t_1},K_{t_2}

Figure 4: Italian university trajectories

Table 7: Path coefficients

	From–>To	Value	Value Bootstrap	S.E.	t	Pr >$\|t\|$
	β_{0lin}	1,53	0,00	1,66	0,92	0,37
K_{lin}	K_{int} –> K_{lin}	1,07	0,96	0,05	20,91	0,00
	β_{0kt_1}	-1,57	0,00	3,01	-0,52	0,61
K_{t_0}	K_{int} –> K_{t_0}	0,86	0,90	0,09	9,34	0,00
	β_{0kt_1}	3,50	0,00	3,03	1,16	0,26
	K_{int} –> K_{t_1}	33,58	16,51	4,83	6,95	0,00
	K_{lin} –> K_{t_1}	-20,81	-9,93	3,13	-6,64	0,00
K_{t_1}	K_{t_0} –> K_{t_1}	-11,86	-6,68	1,73	-6,85	0,00
	β_{0kt_2}	2,32	0,00	0,64	3,62	0,00
	K_{int} –> K_{t_2}	-0,06	-0,05	0,07	-0,82	0,42
	K_{lin} –> K_{t_2}	2,41	2,39	0,07	36,51	0,00
K_{t_2}	K_{t_1} –> K_{t_2}	-1,42	-1,75	0,03	-47,82	0,00
	β_{0BSt_0}	12,02	0,00	3,84	3,13	0,00
BSt_0	K_{t_0} –> BSt_0	0,91	0,75	0,14	6,32	0,00
	β_{0CSt_0}	-7,56	0,00	2,32	-3,26	0,00
CSt_0	K_{t_0} –> CSt_0	1,06	0,94	0,09	12,28	0,00
	β_{0BSt_1}	7,68	0,00	2,36	3,25	0,00
BSt_1	K_{t_1} –> BSt_1	1,00	0,91	0,08	11,92	0,00
	β_{0CSt_1}	-5,41	0,00	1,69	-3,21	0,00
CSt_1	K_{t_1} –> CSt_1	1,00	0,96	0,06	16,58	0,00
	β_{0BSt_2}	16,24	0,00	3,81	4,26	0,00
BSt_2	K_{t_2} –> BSt_2	0,82	0,91	0,08	10,63	0,00
	β_{0CSt_2}	-13,48	0,00	3,20	-4,21	0,00
CSt_2	K_{t_2} –> CSt_2	1,15	0,95	0,07	17,64	0,00

and the rates of gains in performances can be regarded as distinct factors in describing school learning trajectories we can assert that our goal has been achieved.

4 Conclusions and closing remarks

The aims of this paper have been, on the one hand, to offer a new perspective on the use of results from progress tests for benchmarking efforts, and, on the other, to demonstrate how PLS-PM could assist us in the analysis of growth curves. Using progress tests for benchmarking efforts, the effectiveness of an instructional approach might be

captured by the ability to "lift" comparatively low-performing students to the level of students with higher initial ability. In contexts where performance indicators are very important, the information obtained from progress tests may indeed constitute an additional criterion for judging the effectiveness of a particular institution or curriculum. The study contributes to the confirmation of a thesis already present in the literature, according to which a substantial amount of variation can be attributed to different rates in the growth of knowledge across medical schools. From a methodological point of view, we have demonstrated that the PLS-PM approach can be successfully used to estimate growth curves. Using PLS-PM we have the best estimation of the measurement model without any problem concerning its identification. The possibility of applying the PLS-PM approach with a small sample has allowed us to estimate the growth curve with only 29 units.
The study presented in this paper has several limitations. An immediate problem to note is that progress tests in Italy are optional and used only as a summative assessment. This could lead to misleading results as it is a self-selected sample. Future research should be based on mandatory tests for all. The second limit is linked to the availability of data. We had access to aggregate data, so the unit of analysis is the university, that is, the synthesis of the elementary data that are represented by the students. It would have been more appropriate to work with disaggregated data, in such a way as to have the individual student as the unit of analysis and thus the raw, not synthesized, data.

The third aspect concerns the single cohort analyzed for three years. This work analyzes the only cohort available for only three years. If we had had the availability of other cohorts we could have made comparisons among different cohorts and understand if there were differences in student learning and among growth curves.
In the end, the tests were not administered in the 2020 due to the Covid-19 pandemic. To date, we are unable to establish whether failure to administer due to force majeure had a negative impact on the results. Future research is needed to recognize this impact.

Despite these limitations, this study provides an additional argument for the validity of the use of progress testing used for benchmarking efforts. The work wants to emphasize that the creation and implementation of the progress test is among the most important actions promoted by Italian Conference of the Presidents of the Undergraduate Medical Curriculum. The analysis, however, highlights the weaknesses that need to be strengthened to ensure that it can be a valid tool to be provided to the various universities not only for the acquisition of information on students' transversal skills but also for an interpretation of their disciplinary skills. We hope that this preliminary study will inspire further research on these important but largely understudied processes.

References

Aarts, R., Steidel, K., Manuel, B.A. et al. (2010) Progress testing in resource-poor countries: a case from Mozambique.*Medical Teacher*, 32 (6), 461-463.

Albano, M.G., Cavallo, F., Hoogenboom, R. et al. (1996) An international comparison of knowledge levels of medical students: the Maastricht Progress Test. *Medical Education*, Wiley Online Library, 30(4), 239-245

Ali, K., Coombes, L., Kay, E. et al. (2016) Progress testing in undergraduate dental education: the peninsula experience and future opportunities. *European Journal of Dental Education*, 20 (3): 129-134.

Becker, J.M. and Ismail, I.R. (2016) Accounting for sampling weights in pls path modeling: Simulations and empirical examples. *European Management Journal*, 34 (6): 606-617.

Bentler, P.M. and Huang, W. (2014) On components, latent variables, pls and simple methods: Reactions to Rigdon's rethinking of pls. *Long Range Planning*, 47 (3): 138-145.

Berlin, K.S., Parra, G.R. and Williams, N.A. (2014) An introduction to latent variable mixture modeling (part 2): longitudinal latent class growth analysis and growth mixture models, *Journal of Pediatric Psychology*, Oxford University Press, 39(2), 188-203.

Bollen, K.A. and Curran, P.J. (2006) *Latent curve models: A Structural Equation Perspective*, 467, John Wiley & Sons.

Bollen, K.A. (1989) *Structural Equations with Latent Variables*. Wiley. New York.

Bolton, R.N. and Drew, J.H. (1991) A longitudinal analysis of the impact of service changes on customer attitudes. *Journal of Marketing*, 55 (1): 1-9.

Caspersen, J. and Smeby, J-C. (2020) Placement training and learning outcomes in social work education. *Studies in Higher Education*, Routledge, 1-14

Cataldo, R., Grassia M.G., Lauro, N.C. et al. (2017) Developments in higher-order pls-pm for the building of a system of composite indicators. *Quality & Quantity*,51 (2): 657-674.

Chen, Y., Henning, M., Yielder, J., Jones, R., Wearn, A. and Weller, J. (2015) Progress testing in the medical curriculum: students' approaches to learning and perceived stress. *BMC Medical Education*, 15(1): 1-8.

Chin, W.W. and Newsted, P.R. (1999) Structural equation modeling analysis with small samples using partial least squares. *Statistical Strategies for Small Sample Research*, 1 (1): 307-341.

Ciavolino E. (2012) General distress as second order latent variable estimated through PLS-PM approach. *Electronic Journal of Applied Statistical Analysis*, 5(3), 458–464

Ciavolino, E. and Nitti, M.(2013) Simulation study for PLS path modelling with high-order construct: A job satisfaction model evidence. *Advanced dynamic modeling of economic and social systems*, Springer, 185-207

Ciavolino, E. and Nitti, M. (2013) Using the hybrid two-step estimation approach for the identification of second-order latent variable models. *Journal of Applied Statistics*, **40**, 508-526

Ciavolino, E., Carpita, M. and Nitti, M. (2015) High-order pls path model with qualitative external information. *Quality & Quantity*, **49**, 1609-1620

Ciavolino, E., Ferrante, L., Sternativo, G., Cheah, J., Rollo, S., Marinaci, T. and

Venuleo, C. (2022) A confirmatory composite analysis for the Italian validation of the interactions anxiousness scale: a higher-order version. *Behaviormetrika*, **49**, 23-46

Ciavolino, E., Aria, M., Cheah, J. and Roldán, J. (2022). A tale of PLS structural equation modelling: episode I—a bibliometrix citation analysis. *Social Indicators Research*, **164**, 1323-1348

Crocetta, C., Brindisi, M., Lo Muzio, L. et al. (2018) Analisi dei risultati del progress test 2017 dei corsi di laurea in odontoiatria e protesi dentaria.

Curran, P.J. (2003) Have multilevel models been structural equation models all along?. *Multivariate Behavioral Research* 38 (4): 529-569.

Dijkstra, T.K. and Henseler, J. (2015) Consistent and asymptotically normal PLS estimators for linear structural equations. *Computational Statistics & Data Analysis*, 81, 10-23.

Dijkstra, T.K. and Henseler, J. (2015) Consistent partial least squares path modeling. *MIS Quarterly*, 39 (2).

Dijkstra, T.K. and Schermelleh-Engel, K. (2014) Consistent partial least squares for nonlinear structural equation models. *Psychometrika*, 79 (4): 585-604.

Dijkstra, T.K. (2014) PLS' Janus face–response to professor Rigdon's "rethinking partial least squares modeling: in praise of simple methods". *Long Range Planning*, 47 (3), 146-153.

Duncan, T.E., Duncan, S.C. and Strycker, L.A. (2013) *An introduction to latent variable growth curve modeling: Concepts, issues, and application.* Routledge.

Fornell, C. and Cha, J. (1994) Marketing research. JMR, *Journal of Marketing Research*, 33 (1), 121.

Fornell, C. and Bookstein, F.L. (1982) Two structural equation models: Lisrel and pls applied to consumer exit-voice theory. *Journal of Marketing Research*, 19 (4): 440-452.

Freeman, A., Van Der Vleuten, C., Nouns, Z. et al. (2010) Progress testing internationally. *Medical Teacher*, 32 (6): 451-455.

Gallo P. (2018) Cosa cambia con la laurea abilitante per la Professione medica Tra progress test e training test. *Med. Chir*, 79, 3524

Gefen, D., Rigdon, E.E. and Straub, D. (2011) Editor's comments: an update and extension to sem guidelines for administrative and social science research. *Mis Quarterly*,: iii-xiv.

Geiser, C., Bishop, J., Lockhart, G., Shiffman, S. and Grenard, J.L. (2013) Analyzing latent state-trait and multiple-indicator latent growth curve models as multilevel structural equation models, *Frontiers in Psychology*, Frontiers, 4, 975.

Goldstein, H. (2011) Multilevel statistical models. *John Wiley & Son*, 922.

Hair, Jr J.F., Sarstedt, M., Ringle, C.M. et al. (2017) *Advanced issues in partial least squares structural equation modeling.* Sage Publications.

Hair,J.F., Henseler, J., Dijkstra, T.K. et al. (2014) Common beliefs and reality about partial least squares: comments on Rönkkö and Evermann.

Hair, J.F., Sarstedt, M., Ringle, C.M. et al. (2012) An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, 40 (3): 414-433.

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2011) Pls-sem: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, 19 (2): 139-152.

Hair, J.F., Black, W.C., Babin, B.J. et al. (1998) *Multivariate Data Analysis*, 5. Prentice hall Upper Saddle River, NJ.

Henseler, J. and Chin, W.W. (2010) A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. *Structural Equation Modeling*, 17 (1): 82-109.

Henseler, J., Ringle, C.M. and Sinkovics, R.R. (2009) The use of partial least squares path modeling in international marketing. In *New Challenges to International Marketing*. Emerald Group Publishing Limited, 277-319.

Hox, J. and Stoel, R.D. (2005) Multilevel and SEM approaches to growth curve modeling. *Encyclopedia of Statistics in Behavioral Science*, Citeseer.

Hox, J. (2002) The basic two-level regression model: introduction. *Multilevel Analysis: Techniques and Applications*, Lawrence Erlbaum Associates, Mahwah, New Jersey, 10-33.

Johnson, M.D., Herrmann, A. and Huber, F. (2006) The evolution of loyalty intentions. *Journal of Marketing*, 70 (2): 122-132.

Jones, E., Sundaram, S. and Chin, W. (2002) Factors leading to sales force automation use: A longitudinal analysis. *Journal of Personal Selling & Sales Management*, 22 (3): 145-156.

Jöreskog, K.G. and Wold, H.O. (1982) *Systems under indirect observation: Causality, structure, prediction*, 139. North Holland.

Jöreskog, K.G. and Van Thillo, M. (1972) Lisrel: A general computer program for estimating a linear structural equation system involving multiple indicators of unmeasured variables.

Jung, S. and Park, J. (2018) Consistent partial least squares path modeling via regularization.*Frontiers in Psychology*, 9, 174.

Kaplan, D. (2008) *Structural equation modeling: Foundations and extensions*, 10. Sage Publications.

Karay, Y. and Schauber, S.K. (2018) A validity argument for progress testing: Examining the relation between growth trajectories obtained by progress tests and national licensing examinations using a latent growth curve approach. *Medical Teacher*, 40 (11): 1123-1129.

Kessler, R.C. and Greenberg, D.F. (1981) Models of Quantitative Change. *Linear Panel Analysis.*

Lauro, N.C, Grassia, M.G. and Cataldo, R. (2018) Model based composite indicators: New developments in partial least squares-path modeling for the building of different types of composite indicators. *Social Indicators Research*, 135 (2): 421-455.

Lohmöller, J.B. (2013) *Latent variable path modeling with partial least squares.* Springer

Science & Business Media.

McArdle, J.J. (1988) Dynamic but structural equation modeling of repeated measures data. In *Handbook of Multivariate Experimental Psychology*, Springer, 561-614.

Meredith, W. and Tisak, J. (1990) Latent curve analysis. *Psychometrika*, 55 (1): 107-122.

Oliver, R.L. (1980) A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research*, 17 (4): 460-469.

Rajala, R. and Westerlund, M. (2010) Antecedents to consumers' acceptance of mobile advertisements-a hierarchical construct pls structural equation model. In *2010 43rd Hawaii International Conference on System Sciences*. IEEE, 1-10.

Rasbash, J., Browne, W., Goldstein, H. et al. (2000) *A users guide to mlwin, version 2.1, multilevel models project*. Institute of Education, University of London, 105-106.

Recchia, L., Moncharmont, B. and Galloa, P. (2019) Dal progress test al training test: una prima elaborazione dei dati.

Reinartz, W., Haenlein, M. and Henseler, J. (2009) An empirical comparison of the efficacy of covariance-based and variance-based sem. *International Journal of Research in Marketing*, 26 (4): 332-344.

Rigdon, E.E. (2014) Rethinking partial least squares path modeling: In praise of simple methods. *Long Range Planning*, 47 (3): 161-167.

Ringle, C.M., Wende, S., Becker, J.M. et al. (2015) Smartpls 3 *Boenningstedt: SmartPLS GmbH.*

Roemer, E. (2016) A tutorial on the use of pls path modeling in longitudinal studies.*Industrial Management & Data Systems*, 116 (9): 1901-1921.

Schuberth, F., Henseler, J. and Dijkstra, T.K. (2018) Partial least squares path modeling using ordinal categorical indicators. *Quality & Quantity*, 52 (1): 9-35.

Schuwirth, L.W. and Van der Vleuten, C.P. (2012) The use of progress testing. *Perspectives on Medical Education*, 1 (1): 24-30.

Selig, J.P. and Little, T.D. (2012) Autoregressive and cross-lagged panel analysis for longitudinal data.

Shea, C.M. and Howell, J.M. (2000) Efficacy-performance spirals: An empirical test. *Journal of Management*, 26 (4): 791-812.

Singer, J.D., Willett, J.B. et al. (2003) Applied longitudinal data analysis: Modeling change and event occurrence. Oxford university press.

Sarstedt, M., Hair Jr, J.F., Nitzl, C. Ringle, C.M. and Howard, M. (2020) Beyond a tandem analysis of SEM and PROCESS: use of PLS-SEM for mediation analyses! *International Journal of Market Research*, SAGE Publications Sage UK: London, England, 62(3), 288-299.

Sarstedt, M., Hair Jr, J.F., Cheah, J.H., Becker, J.M. and Ringle, C.M. (2019) How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian Marketing Journal (AMJ)*, Elsevier, 27(3), 197-211.

Sarstedt, M., Henseler, J. and Ringle, C.M. (2011) Multigroup analysis in partial least squares (pls) path modeling: Alternative methods and empirical results. In *Measure-*

ment and Research Methods in International Marketing, Emerald Group Publishing Limited, 195-218.

Stoel, R.D., Van den Wittenboer, G. and Hox, J. (2004) Methodological issues in the application of the latent growth curve model. In *Recent Developments on Structural Equation Models*, Springer, 241-261.

Swanson, D.B., Holtzman, K.Z., Butler, A. et al. Collaboration across the pond: the multi-school progress testing project. *Medical Teacher*, 32 (6): 480-485.

Tenenhaus, M., Vinzi, V.E., Chatelin, Y.M. et al. (2005) Pls path modeling. *Computational Statistics & Data Analysis*, 48 (1): 159205.

Tenore, A., Basili, S. and Lenzi, A. (2016) Il progress test 2016. *Medicina e Chirurgia*, 75: 3386–3390.

Tio, R.A., Schutte, B., Meiboom, A.A. et al. (2016) The progress test of medicine: the dutch experience. *Perspectives on Medical Education*, 5 (1): 51-55.

Van der Vleuten, C., Norman, G. and De Graaff, E. (1991) Pitfalls in the pursuit of objectivity: issues of reliability. *Medical education*, 25 (2): 110-118.

Van der Vleuten, C., Freeman, A. and Collares, C.F. (2018) Progress test utopia. *Perspectives on Medical Education*, 7 (2): 136-138.

Vattøy, K.D., Gamlem, S. M .and Rogne, W.M. (2020) Examining students' feedback engagement and assessment experiences: a mixed study. *Studies in Higher Education*, Routledge, 1-13

Vinzi Esposito, V., Chin, W.W., Henseler, J. et al. (2010) *Handbook of partial least squares: Concepts, methods and applications.* Heidelberg, Dordrecht, London, New York: Springer.

Willett, J.B. and Sayer, A.G. (1994) Using covariance structure analysis to detect correlates and predictors of individual change over time. *Psychological Bulletin*, 116 (2): 363.

Wilson, B. (2010) Using pls to investigate interaction effects between higher order branding constructs. In *Handbook of Partial Least Squares.* Springer, 621-652.

Wold, H. (1985). Partial least squares. S. Kotz and NL Johnson (Eds.), *Encyclopedia of Statistical Sciences* (vol. 6). Wiley, New York.

Wold, H. (1982) Soft modeling: the basic design and some extensions. *Systems Under Indirect Observation*, 2: 343.

Wold, H. (1975) Path models with latent variables: The nipals approach. In *Quantitative Sociology.* Elsevier, 307-357.

Wrigley, W., Van Der Vleuten, C.P., Freeman, A. et al. (2012) A systemic framework for the progress test: strengths, constraints and issues: Amee guide no. 71. *Medical Teacher*, 34 (9): 683-697.

Zhang, Z., Hamagami, F., Lijuan Wang, L. et al. (2007) Bayesian analysis of longitudinal data using growth curve models. *International Journal of Behavioral Development*, 31(4): 374-383.