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# ESSENTIAL SKILLS FOR DATA-DRIVEN PROJECT MANAGEMENT:

## A CLASSROOM TEACHING EXPERIMENT

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**Abstract:** We investigate the performance of students in a Data-driven Project Management course module that consists of several realistic case studies derived from the book "The data-driven project manager: A statistical battle against project obstacles" (Vanhoucke 2018). Based on case study evaluations, we monitor the students' level for various technical and non-technical skills. We identify and classify seven project management skills in management literature and, subsequently, we statistically investigate the link between these skills and the student performance during the course module. Also, a model to incorporate these skills in the Dynamic Scheduling framework is proposed and validated using Structural Equation Modeling. The results indicate that planning is key for good risk analysis and project control, and show that both types of skills are important for successful project management.

### INTRODUCTION

In many sectors, project management (PM) is now part of the business and increasingly important for corporate success due to projectization of organizations. Business activities are executed within projects that are grouped in portfolios and managed in programs. Project management is a dynamic process of planning, analysing and controlling a complex set of activities and resources in order to achieve pre-defined objectives. Successful PM requires the careful recruitment and development of skilled project managers (Liikamaa 2015). Given the increasing importance of projects, PM education is in high demand in projectized businesses. The education of future project managers is entrusted to universities and higher education entities, while current project managers can improve their PM skills through seminars and in-company training. One of the greatest challenges of the educational system in the future (both higher education and company trainings) is to determine the focus of PM education since there is little agreement amongst training program institutions on the skills of a good project manager (El-Sabaa 2001). First of all, many researchers are convinced that focusing solely on technical competencies is insufficient since managing projects successfully nowadays requires a mixture of skills such as communication, problem-solving and teamwork (Fisher 2011). Also, Meier, Williams, and Humphreys (2000) investigate the soft skills gap of SMET (Science, Mathematics, Engineering and Technology) students as it is perceived by professionals. The authors observe that certain competencies are currently underdeveloped in an academic context, such as information sharing, cooperation and teamwork skills. In the past decades, however, the PM literature and discipline appears to place more emphasis on hard (technical) skills at the expense of the soft (human) skills, although this trend has slightly changed in the past years. Professional or transversal skills are interchangeable terminology for soft skills, however, we will refer to soft or human skills in the remainder of this manuscript. Pant and Baroudi (2008) highlight the need for a balance between hard and soft skills within PM education at universities and Belzer (2001) also identifies soft skills as the 'missing link' critical to project success. Secondly, the educational system highly focuses on the development of general skills without considering how these competencies are perceived and prioritized in different disciplines (Chan, Zhao, and Luk 2017). Some programs have therefore developed novel approaches that deviate from the standard classroom-teaching sessions by using case studies and business games in order to better educate students a mix of hard and soft skills. Key in case-based learning is that students take an active, rather than a passive, role in the learning process as new knowledge is better absorbed in combination with new and existing experiences. Also, simulation-based business games and case studies might give students the teamwork experience needed to manage the dynamics of changing project conditions (Duncan 1993). Vanhoucke (2014a) shows how research on integrated project management and control has been used in classroom teaching sessions in order to actively stimulate students to participate in small project teams. The research focuses on the integration between the theory of academic research and the practice of teaching activities at several universities. Also, Vanhoucke (2014b) shows how an active learning environment for a PM course module has been designed for business and civil engineering students at Ghent University. The aim of the research is to illustrate how a combination of PM techniques, such as software tools and business games, can be used in classroom teaching sessions to increase student participation and interaction. Stimulating the interaction between students as well as the interaction between students and professionals will lead to an increased engagement, enthusiasm and involvement on the short term and an improved learning experience on the long term.

Most PM programs in universities have been focusing on the technical skills to achieve project success such as the knowledge of the dynamic scheduling (DS) model to understand project scheduling, risk analysis and project control. The DS model focuses on the integration of baseline scheduling, risk analysis and project control in order to deliver projects on time and within budget to the client (Vanhoucke 2012). In our opinion, educators should aim to improve both technical skills - since knowledge transfer is a key function of education programs - and soft skills that allow project managers to effectively apply these technical skills. Hence, we are convinced that no trade-off exists between the focus on hard and soft skills, rather both types of skills should reinforce one another. Therefore, we have analysed a case-based data-driven project management (DDPM) course that requires students to use both their technical skills (knowledge about dynamic scheduling) and human skills (communication, criticality, etc.). The objective of the course module is to provide technical education at an academic level and improve a combination of hard and soft skills that are required in the professional world in order to educate students in their role as future project managers. The DDPM course is explained in detail in Vanhoucke (2018). In this book, the author presents a decision-making tool, called DDPM, which has been developed in an academic context and taught at various business schools. In an interactive way, it is shown how different PM tools based on the DS framework - such as simulations - can be used to successfully complete a project under uncertainty. The author highlights the need for a balance between hard and soft skills within PM education at universities.

In this research, we present three experiments resulting in three main research contributions. First of all, we analyse the results of students throughout the course module in order to determine the influence of the skill levels on the students' performance throughout the course module. More precisely, the first experiment investigates the necessity of the different skills to deliver good results in the case studies. Secondly, we determine the impact of the case-based approach on the different skills and thus investigate to what degree students learn different skills throughout the course module. As a result, the second experiment analyses whether the course module is properly designed. In the third experiment, we are able to validate the DS framework using the evaluation of the students throughout the course module since the course module is completely integrated within this framework.

## LITERATURE

The skill set required for project success has broadened and has changed drastically in the past few years. In order to constantly align education programs with the practical requirements of employers, many researchers aim to identify and classify key skills and competences in the field of PM.

Katz (1955) presents a well-known classification framework for types of skills and identifies three skill types that can be developed independently: human, conceptual and technical skills. This basic framework is used in many studies that investigate the impact of skills on the PM practices in both the professional and academic community. Hence, we will categorize the different skills that are discussed in various research papers based on these three general skill types. In table 1, there are three columns to indicate which skills in the corresponding research papers belong to, respectively, the technical, human and conceptual skills.

The Eye of Competence is a framework supported by IPMA (2015) that identifies a total of 92 subcategories of skills - 46 competences and 46 experiences - covering three areas: 20 technical, 11 contextual and 15 behavioral competence subcategories. These three skill areas overlap to a large degree with the skills discussed by Katz (1955): technical competences & technical skills, behavioral competences & human skills and contextual competences & conceptual skills. However, both frameworks result in conflicting outcomes for the classification of certain skills. For example, table 1 shows that teamwork and problem resolution are identified as technical skills in the IPMA framework, where they could be categorized as human skills. Also, creativity is considered a behavioral skill, although it could be identified as a conceptual skill. De Los Ríos-Carmenado, Rodriguez López, and Pérez García (2015) make use of the IPMA (2015) framework to show that students improve the three types of skills through project-based learning methodology. A large portion of students achieved a high competence development of skills mainly related to teamwork such as creativity, leadership and negotiation skills. The authors show that the contextual skills result in the largest improvement, the second largest improvement is obtained for the technical skills and the least improvement for the behavioral skills. Walther et al. (2011) extend the three clusters of competencies - self, contextual and technical skills - with four other clusters: flexibility, interaction, plan and professional realities. The authors identify a complex learning process for the professional formation of engineering students that consists of both an explicit learning environment and various other influences. The proposed contextual model shows that the learning activities and the learning environment result in both accidental and intended competencies.

In some research studies, the list of professional competences is divided into only two groups, soft and hard skills, rather than three groups. The hard skills refer to the technical skills, while the soft skills cover both human and conceptual skills. Kloppenborg and Petrick (1999) suggest that relationship skills complement the effectiveness of technical skills because project outcomes are achieved through people using their knowledge and creativity.

In this study, we determine a set of seven PM-related skills. This set is obtained from our assessment of the skills needed to successfully complete the course module as well as the literature review presented in this section. The seven PM-related skills are highlighted in bold in **table 1**. In figure 1, we categorize the seven skills based on the three types of skills introduced above. The different skills are briefly discussed along the following lines, and will be used in the remainder of the study.

| Katz (1955) | **Technical** | **Human** | **Conceptual** |
|---|---|---|---|
| Mantel et al. (2004) | Technical | **Communication**<br>Team building<br>Leadership<br>Coping | **Organizational** |
| Belzer (2001) | | **Communication**<br>Team building<br>Leadership | **Organization**<br>Problem solving and decision-making<br>**Creativity**<br>Flexibility |
| Edum-Fotwe and McCaffer (2000)<br>Odusami (2002)<br>Gushgari, Francis, and Saklou (1997)<br>Fraser (1999)<br>Tett et al. (2000) | Technical | Delegation<br>Team working<br>Leadership<br>Human behavior<br>Stress handeling | Report writing<br>Problem solving<br>Decision making |
| El-Sabaa (2001) | Knowledge tools and techniques<br>**Understanding**<br>Technology requirements | **Communication**<br>Authority<br>Enthusiasm | **Organizing**<br>Problem-oriented<br>Planning |
| Fisher (2011) | | Understanding behavior<br>Leading others<br>Conflict management<br>Influencing others<br>Empowerment | Cultural awareness |
| Muller and Turner (2007) | **Critical analysis and judgment** | Initiative<br>Leadership<br>Collaboration<br>Conflict management<br>**Communication** | |
| Liikama (2015) | **Analytical thinking** | Motivation<br>Influence<br>Self-awareness<br>Emotional resilience<br>Intuitiveness<br>**Communication** | Achieving |
| Boyazis (2008) | **System thinking**<br>Pattern recognition | Self-management<br>Self-awareness<br>Social awareness<br>Empathy | |

Table 1 Literature review of skills grouped in different skill types.

- **Understanding** is a skill that indicates whether people fully comprehend the idea behind methods, processes, procedures as well as their assumptions, limitations and contributions.
- **Analysis** allows people to break down problems into subproblems and systematically diagnose them using rational principles. Liikamaa (2015) refers to this skill as 'Analytical thinking', where Boyazis (2008) focuses on the systematical element in the definition and refers to 'Systems thinking'.
- **Calculus** reflects the closeness of a measured, estimated or calculated value compared to its actual value. This skill thus reflects the correctness of the applied methods and the resulting calculations.
- **Communication** is the ability to openly listen to opposing views and clearly convey complex ideas and thoughts with the aim of improving.
- **Criticality** requires taking outside knowledge into account while evaluating information with the aim of making a sound judgment.
- **Holistic** implies a broader view based on knowledge of the different components of a project, portfolio or company in relation to the whole organization. Hence, many researchers refer to this skill as 'organization'.
- **Creativity** corresponds with the ability to adopt techniques and general concepts to the needs of a specific situation. Creativity thus includes out-of-the-box thinking as well as flexible and effectively changing your toolbox for the best fit with each situation.

Based on teaching experiences in different business schools and many years of academic research, a DDPM course has been designed in such a way that a mix of the seven skills is necessary (Vanhoucke 2018). In the current paper, we will test whether these seven skills are indeed essential for successful DDPM. In **figure 1**, we label the seven skills as hard or soft skills and as technical, human and conceptual skills. In this section, these skills were described in a very general way, however, they will be discussed in more detail in the next section.

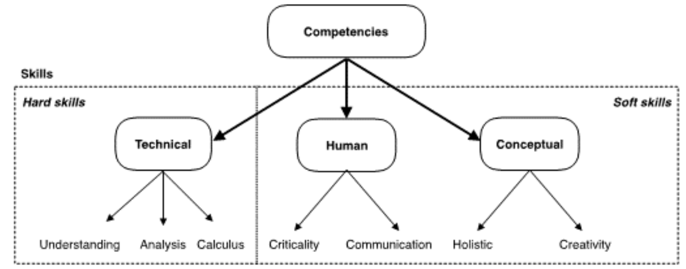


Figure 1 Overview of skills investigated in this research

## RESEARCH STUDY

In this section, a summary is given of the data-driven project management course module, and it is shown how we have validated the skills required to successfully complete this course module in our research study.

### Course module

The data-driven project management course module consists of four sessions in which the students have to work in groups of 3 to 5 people in order to solve a set of sequential case studies related to different aspects of project management based on the dynamic scheduling (DS) framework proposed in Vanhoucke (2012). This framework assumes that project scheduling, risk analysis and project control should be integrated to increase the likelihood of project success, i.e., finishing the project within time, cost and scope. The course module requires students to solve four case studies, and each case study focuses on one of the three components (schedule, risk and control) of the DS framework and a simulation game (**figure 2**). The outline of the course module can be briefly summarized as follows. Each group of students has presented a unique case study that considers a (fictitious) company responsible for a set of projects. The projects are based on real-life data but have been adjusted and simplified such that different aspects of the project can be analysed within four sessions, and the different case studies have a similar degree of complexity.

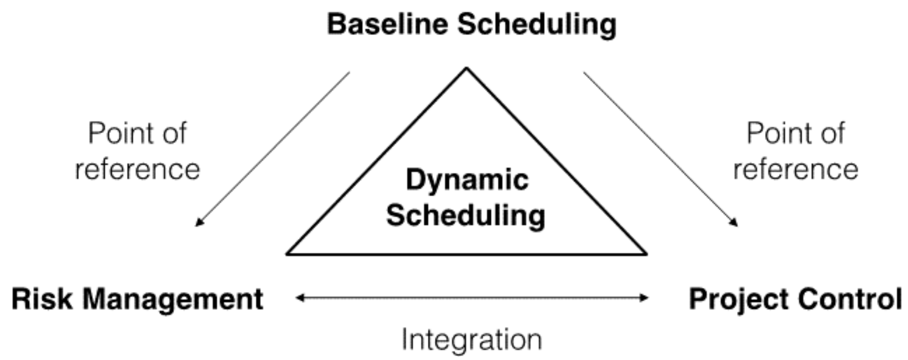


Figure 2 Dynamic scheduling model (Vanhoucke, 2012)

In the **first session**, the students are introduced to the techniques of scheduling projects, and concepts such as the Critical Path Method (CPM) and the Program Evaluation and Review Technique (PERT) are explained in detail. Afterwards, the students are responsible for the construction of schedules for two project proposals. Hence, they have to apply the PERT/CPM methodology to analyse both projects and they have to compare the schedules of the different projects in order to select one of the two project proposals.

In the **second session**, the students receive a second case study that builds upon the first case study, as they are now responsible for managing one of the two project proposals. In this case study, the students are responsible for controlling the project and taking actions under uncertainty by means of the simulation game "The Project Scheduling Game (PSG)" (Vanhoucke, Vereecke, and Gemmel 2005) that imitates the project progress. The main reason why the simulation game is held in the second session is to create awareness to students that knowledge about a project schedule (obtained after solving case study 1) is not enough to deliver projects successfully to the client, and that some awareness of the expected risk (that they will gain in case study 3) as well as having access to some formal control systems (provided in case study 4) are necessary. This idea fits perfectly in the DS framework, which shows that the project schedule is a point of reference for risk analysis and project control. For this very reason, the simulation game is held after the first session and before the third session (schedule risk analysis) and the fourth session (project control).

In the **third session**, the case study deals with the interpretation of different expected risk factors known prior to the project start. In this case study, the students have to evaluate five different proposals that aim at reducing the risk by analysing the potential impact of risk on the project objective using the schedule as input. This technique is known as schedule risk analysis (SRA) and makes use Monte Carlo simulations to provide the students with sensitivity metrics such as the criticality index (CI) and others.

In the **fourth session**, it is assumed that the project is in progress and students are responsible for monitoring and controlling the progress in order to deliver the projects on time and within budget to the client. To that purpose, students have to analyse and assess the status of the project at a milestone period (after 10 weeks progress) and report possible actions in case that the project objectives are in danger. This session introduces the well-known Earned Value Management (EVM) methodology, and stimulates the students to use this method for proposing actions. The EVM method is discussed in detail in Vandevoorde and Vanhoucke (2006), in which the authors compare the project duration forecasts of three EVM methods. This session is often a challenge to students since EVM looks like a set of (relatively) simple formulas, but is therefore not always easy to use and interpret.

The four written reports (one for each case study) are evaluated by the lecturer (see 'Course evaluation') and different evaluation criteria are discussed and linked to the different skills presented earlier (see 'Student skills').

## Course evaluation

After each of the four sessions, the students need to hand in a single-page written report in order to support their decisions to the board of directors (consisting of the lecturer and a research assistant) of the fictitious company. The report should summarize the proposed strategy, the corresponding analysis and the main conclusions in a short and comprehensive way. This report is used to score the different groups on their knowledge about the different aspects of PM (PERT, PSG, SRA, EVM).

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## Student skills

Based on an intense search in the literature (see section 2) as well as our assessment of the necessary skills a project manager should possess in order to manage projects successfully, we have linked the different skills of **figure 1** to different evaluation criteria. We have defined criteria for evaluating the different skills in order to have a fair comparison between student groups for each case study. A summary of the evaluation criteria is given in **table 2** under the column "Evaluation criteria" for each of the four sessions (PERT, PSG, SRA, EVM). When the body of the table displays an 'X', we assume that the skill is

| Case study | Evaluation criteria | Skills | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | UNST | ANLY | CREA | HOLI | CALC | CRIT | COMM |
| PERT | Problem statement | X | | | X | | | |
| | Schedule analysis | | X | | X | X | | |
| | Key findings | | X | | | X | X | X |
| | Recommendations | | | X | | | | X |
| PSG | Solution (time and cost) | | X | | X | X | | |
| | Strategy | X | X | X | | | X | X |
| | Limitations | X | | X | | | X | X |
| SRA | Project plan | X | | | X | | | |
| | Analysis proposals | | X | | X | X | | |
| | Analysis general conclusions | X | X | X | X | X | X | X |
| | Recommendations | | | X | | | | X |
| EVM | Project resources | X | X | | X | | | X |
| | Project budget | X | X | | X | X | | |
| | Analysis key metrics | | X | | X | X | | |
| | Analysis performance indicators | | X | | X | X | X | X |
| | Analysis forecasts | X | | X | | | X | |
| | Recommendations | | | X | | | | X |

Table 2 Link between aspects of cases and skills

necessary to perform well for this criteria, while a blank space means that this specific skill is not particularly relevant for the corresponding criteria. The definition for each skill has been presented earlier but is now outlined in detail with reference to the four case studies:

- **Understanding (UNST)** We test the understanding of the students with respect to the different PM methodologies of the four case studies (PERT, PSG, SRA, and EVM) as well as their understanding of the (dis)advantages of the different methodologies and the link with their specific case study.
- **Analysis (ANLY)** The computations in the case studies should be based on well-considered assumptions and should be done under different scenarios in order to allow a certain level of sensitivity analysis.
- **Calculus (CALC)** The students need to understand the principles of basic mathematics and statistics in order to analyse uncertainty in the project. Also, the calculations should be done in a correct way and the formulas should be understood completely to ensure a correct interpretation of the outcomes. In case that data is missing or time is limited, the students should be able to use the available data in the best possible way.
- **Communication (COMM)** As is typical for case studies that require written reports under time pressure, students have to divide the tasks between the different members of the group. A good and efficient communication within the group is necessary to come up with relevant conclusions before a (pre-defined) strict deadline.
- **Criticality (CRIT)** The conclusions of the students should be interpreted in a critical way and different opinions between the group members should result in different points-of-view rather than one non-critical conclusion. The students should actively avoid group thinking.
- **Holistic (HOLI)** The case studies should be interpreted and analysed as integrated exercise rather than as isolated exercises. The conclusions should consider the results and recommendations presented in previous case studies rather than only solving the problem of each case study in isolation. This is particularly relevant in the risk analysis and project control case study as the baseline schedule created in the first case studies acts as a point-of-reference in these two case studies.
- **Creativity (CREA)** Since the recommendations the students have to make require not only calculations but also a certain degree of creativity, this is also an important skill that is not always measured in traditional course modules. Solving the different case studies in an integrated way under time pressure requires the students to show a high level of creativity.

### Research objectives

Each time the students hand in their report for a case study, the lecturer evaluates this report to score the performance of the students for that specific case study. Using the different criteria in **table 2**, each skill will receive an evaluation score for each case study when an 'X' is shown in the table. The performance of students in the different case studies can thus be linked to the different skills in three experiments, as explained hereafter:

**Experiment 1** investigates the link between the seven skills and the students' performance during the different case studies as well as the complete course module. We aim to test whether the crucial skills for a specific aspect of PM (planning, risk or control) - rated by the lecturers using the different evaluation criteria as shown in **table 2** - are indeed covered by a specific case study in the course module.

**Experiment 2** takes the time aspect into account as we test whether the skills improve along with the course module. Rather than focusing solely on the importance of skills in experiment 1, we want to test whether certain skills improve when the students progress in the course module. This experiment allows us to analyse whether and in which phase of the course module hard skills are more or less important than soft skills.

**Experiment 3** investigates the impact of the seven skills in the four case studies of our course module considering that these case studies are interrelated based on the DS framework. More precisely, the score for one case study that is demonstrated by a limited set of skills is impacted by the scores for other case studies completed earlier in the course module. Hence, this experiment does no longer treats the effect of skill improvement, skill importance and the relation between the case studies in isolation but rather presents an integrated model to identify the important skills for successful project management.

In the remainder of the paper, we make use of the abbreviations SKILL and CASE as follows:

SKILL x = UNST, ANLY, CREA, HOLI, CALC, CRIT or COMM (with x = {1,...,7})

CASE y = PERT, PSG, SRA or EVM (with y = {1, ..., 4})

The lecturer evaluates the skill level in a particular case by using the evaluation criteria and the link to the different skills (marked with 'X') in **table 2**:

SKILL(CASE) = Score for a particular skill x in a particular case study y.

Finally, the lecturer gives a score for each case study resulting in a total score for the course module:

TOT = Total score of the course module is equal to the sum of the scores of the four case studies y.

A summary of the above abbreviations is given in **table 3** and will be explained in more detail in section 4.

Table 3 List of abbreviations

| Abbreviation | Meaning | Abbreviation | Meaning |
|---|---|---|---|
| PERT | Planning case study | UNST | Understanding |
| PSG | Project scheduling game case study | ANLY | Analysis |
| SRA | Schedule risk analysis case study | CREA | Creativity |
| EVM | Project control case study | HOLI | Holistic |
| SKILL(CASE) | Score for the skill in case study | CALC | Calculus |
| TOT | Score for total course module | CRIT | Criticality |
| SKILL(CASE,TOT) | Relation between average skill level in a case study and total score | COMM | Communication |
| SKILL(CASE1,CASE2) | Relation between average skill level in two case studies | | |

## COMPUTATIONAL EXPERIMENTS AND RESULTS

This section presents the methodology used for running the three experiments. More precisely, the data collection is discussed first, followed by a description of our approach for each experiment.

### Data collection

The data required in this study were collected over a three-year time period (2016-2019) in a total of 9 programs in 3 classes (Masters in International Management & Strategy (MIMS), Masters in General Management (MGM) and Master of Science in Management (MSM) in Belgium and the UK. In **table 4**, we show the general information of the nine programs where the data-driven project management course module was educated. A total of 349 students subdivided into 103 groups were involved in the course module. From each group, we have obtained a written report at the end of each case study. Since the students only need to hand in one written report per group and thus they are marked as a group, we have no information on the individual performance of the students. In case that we mention the 'performance' in the remainder of this study, we thus refer to the group performance rather than the performance of an individual student.

### Experiment 1: Impact of skills on performance

In experiment 1, we aim to test which (of the seven) skills are crucial for managing projects successfully. More precisely, the experiment will compare the score for a skill in the four case studies with the total score of the course module. The score for a particular skill for a particular case study SKILL(CASE) is compared

| | Program | Year | Country | #Groups | #Students |
|---|---|---|---|---|---|
| 1 | MIMS | 2016 | Belgium | 11 | 33 |
| 2 | MGM | 2017 | Belgium | 9 | 28 |
| 3 | MSM | 2017 | UK | 8 | 18 |
| 4 | MIMS | 2017 | Belgium | 11 | 33 |
| 5 | MGM | 2018 | Belgium | 6 | 20 |
| 6 | MSM | 2018 | UK | 17 | 68 |
| 7 | MIMS | 2018 | Belgium | 12 | 37 |
| 8 | MGM | 2019 | Belgium | 10 | 31 |
| 9 | MSM | 2019 | UK | 19 | 81 |
| **TOT** | | | | **103** | **349** |

Table 4 Details of the dataset

with the total score TOT as shown in the following equation:

$$\text{SKILL(CASE, TOT)} = \text{SKILL(CASE)} - \text{TOT} \quad (1)$$

Eq.(2) leads to 28 (= 4 x 7) research hypotheses, in general abbreviated as HX.Y, to investigate the impact for each skill x = {1, ..., 7} and each case study y = {1, ..., 4} as follows:

- H0: µxy = 0: The null hypothesis assumes that the score for a particular skill x in a particular case study y is the same as the total score for the course module, and hence assumes that the skill in this case study is an important indicator for the total score of the course module.
- Ha: µxy ≠ 0: The alternative hypothesis assumes that the score for a particular skill x in a particular case study y is much lower or higher than the score for the course module, and hence assumes that the skill in this case study is not a very important indicator for the overall performance during the course module.

## Approach

In this research, we statistically investigate whether the aforementioned true mean differences µxy are equal to zero using a paired t-test. This test allows us to investigate whether the average score for a skill per case study is a good indicator for the overall score in the course module. There exists no expected direction in the deviation of the true mean difference in the alternative hypotheses Ha as both a significant

Prior to using paired sample t-tests, we should check four main assumptions. First of all, the sample data should be continuous and numeric. Since the skills (using the written reports) and the performance of the students are scored on a total of 20 points, the sample data satisfies the first assumption. Secondly, the observations should be independent. Given the data collection process that has been used in this research is done at different universities in different places, we can reasonably assume that this assumption is satisfied. Thirdly, the sample data should pass the normality test. Since the number of data elements is relatively small (n < 2,000), we have conducted the Shapiro-Wilk test to investigate the normality. The results in **table 5** indicate that the null hypothesis - normal distribution - cannot be rejected for most of the data elements (i.e., scores for case studies and skills). For nine data elements (shown in bold in **table 5**), the null hypothesis is rejected at a 95% confidence interval, however, the null hypothesis would not be rejected for six data elements at a 99% confidence interval. In general, the results with respect to these six data elements should be interpreted with care since the normality test is not satisfied in the case that p = 0.05. Finally, no outliers were identified in the data.

## Results

The results of this analysis are shown in **table 6**. A p-value less than 0.05 is statistically significant (indicated in bold in the last column of **table 6**) and thus indicates strong evidence against the null hypothesis H0.





| | Shapiro-Wilk | | | | Shapiro-Wilk | | |
|---|---|---|---|---|---|---|---|
| | Statistics | df | Sig. | | Statistics | df | Sig. |
| **UNST(PERT)** | 0.964 | 103 | **0.007** | HOLI(SRA) | 0.990 | 103 | 0.609 |
| UNST(PSG) | 0.983 | 103 | 0.217 | HOLI(EVM) | 0.993 | 103 | 0.882 |
| UNST(SRA) | 0.990 | 103 | 0.662 | CALC(PERT) | 0.978 | 103 | 0.079 |
| UNST(EVM) | 0.992 | 103 | 0.806 | CALC(PSG) | 0.989 | 103 | 0.555 |
| **ANLY(PERT)** | 0.967 | 103 | **0.012** | **CALC(SRA)** | 0.971 | 103 | **0.022** |
| ANLY(PSG) | 0.979 | 103 | 0.101 | CALC(EVM) | 0.983 | 103 | 0.227 |
| **ANLY(SRA)** | 0.864 | 103 | **0.000** | **CRIT(PERT)** | 0.957 | 103 | **0.002** |
| ANLY(EVM) | 0.992 | 103 | 0.838 | CRIT(PSG) | 0.982 | 103 | 0.189 |
| **CREA(PERT)** | 0.975 | 103 | **0.045** | **CRIT(SRA)** | 0.969 | 103 | **0.016** |
| CREA(PSG) | 0.982 | 103 | 0.189 | **CRIT(EVM)** | 0.973 | 103 | **0.031** |
| CREA(SRA) | 0.983 | 103 | 0.198 | COMM(PERT | 0.977 | 103 | 0.072 |
| **CREA(EVM)** | 0.973 | 103 | **0.035** | ) | 0.982 | 103 | 0.189 |
| HOLI(PERT) | 0.992 | 103 | 0.779 | COMM(PSG) | 0.983 | 103 | 0.216 |
| HOLI(PSG) | 0.991 | 103 | 0.734 | COMM(SRA) | 0.991 | 103 | 0.718 |
| | | | | COMM(EVM) | | | |

Table 5 Output for the normality test

We note that UNST(PERT,TOT) (mean=-0.48; p=0.148) and UNST(EVM,TOT) (mean=-0.24; p=0.212) are good indicators for the total score in the course module, which implies that a low (high) understanding of the problem during planning and project control results in a low (high) score of the course module. In contrast, a high total score in the course module can be obtained despite a lower score for the skill 'Understanding' in the simulation game (UNST(PSG,TOT)) and risk analysis case study (UNST(SRA,TOT)). A similar observation can be made for the skills 'Analysis' and 'Criticality' as H0 cannot be rejected in the project scheduling (ANLY(PERT,TOT), CRIT(PERT,TOT)) and project control (ANLY(EVM,TOT),CRIT(EVM,TOT)) case study given a 95% confidence interval. Furthermore, the level of the skill 'Calculus' in the first case study is closely related to the overall performance during the course module (CALC(PERT, TOT)) (mean=-0.41; p=0.102). Consequently, mistakes in the calculations during planning will result in an equally low total score, while a high degree of correctness of the calculations during planning will pay o↵ in terms of a higher total score. We can thus conclude that accurate planning is important for a successful completion of the course module, i.e. successfully managing the project under uncertainty.

In summary, the results of this analysis show that mainly the hard skills are the drivers for the total score in the first and last session. With respect to the soft skills, the results are more scattered. For example, the skill 'Holistic' is a good indicator for the overall performance in sessions 2 and 3, while a critical mindset is a good indicator for the total score in session 1 (planning) and session 4 (control).

## Experiment 2: Improvement of skills

While experiment 1 statically investigated the impact of the different skills on average and per case study on the overall score of the course module, experiment 2 investigates whether skills improve along with the course module. Such an approach can show us whether or not students learn and develop hard and soft skills throughout the course module. To that purpose, we have compared the scores for each skill at the start of the course module with the scores obtained just after they handed in their last written report, as shown in the following equation:

$$\text{SKILL(PERT,EVM)} = \text{SKILL(EVM)} - \text{SKILL(PERT)} \quad (2)$$

Eq.(3) allows us to measure the improvement for each skill. If some skills are less developed at the beginning of the course module (i.e., after solving the first case

| | Skill per case study | Mean | Std. dev. | Std. error | 95% Confidence interval | | t | df | p-value |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | Lower bound | Upper bound | | | |
| H1.1 | UNST(PERT,TOT) | -0.4755 | 3.3101 | 0.3262 | -1.1224 | 0.1715 | -1.458 | 102 | 0.148 |
| H1.2 | UNST(PSG,TOT) | -0.9560 | 2.5882 | 0.2550 | -1.4619 | -0.4502 | -3.749 | 102 | **0.000** |
| H1.3 | UNST(SRA,TOT) | -0.8250 | 2.2044 | 0.2172 | -1.2558 | -0.3942 | -3.798 | 102 | **0.000** |
| H1.4 | UNST(EVM,TOT) | -0.2360 | 1.9087 | 0.1881 | -0.6090 | 0.1371 | -1.255 | 102 | 0.212 |
| H2.1 | ANLY(PERT,TOT) | -0.3542 | 2.1790 | 0.2147 | -0.7800 | 0.0717 | -1.650 | 102 | 0.102 |
| H2.2 | ANLY(PSG,TOT) | -0.4488 | 1.7751 | 0.1749 | -0.7957 | -0.1018 | -2.566 | 102 | **0.012** |
| H2.3 | ANLY(SRA,TOT) | 1.0489 | 1.2468 | 0.1229 | 0.8052 | 1.2926 | 8.538 | 102 | **0.000** |
| H2.4 | ANLY(EVM,TOT) | 0.2133 | 1.4193 | 0.1399 | -0.0641 | 0.4907 | 1.525 | 102 | 0.130 |
| H3.1 | CREA(PERT,TOT) | 0.3304 | 2.6108 | 0.2573 | -0.1799 | 0.8406 | 1.284 | 102 | 0.202 |
| H3.2 | CREA(PSG,TOT) | -0.9560 | 2.5882 | 0.2550 | -1.4619 | -0.4502 | -3.749 | 102 | **0.000** |
| H3.3 | CREA(SRA,TOT) | -0.2837 | 2.3140 | 0.2280 | -0.7360 | 0.1685 | -1.244 | 102 | 0.216 |
| H3.4 | CREA(EVM,TOT) | 0.0901 | 1.9939 | 0.1965 | -0.2996 | 0.4798 | 0.458 | 102 | 0.648 |
| H4.1 | HOLI(PERT,TOT) | -0.4657 | 2.0867 | 0.2056 | -0.8735 | -0.0579 | -2.265 | 102 | **0.026** |
| H4.2 | HOLI(PSG,TOT) | -0.2039 | 1.9651 | 0.1936 | -0.5880 | 0.1802 | -1.053 | 102 | 0.295 |
| H4.3 | HOLI(SRA,TOT) | 0.2406 | 1.4817 | 0.1460 | -0.0490 | 0.5302 | 1.648 | 102 | 0.102 |
| H4.4 | HOLI(EVM,TOT) | 0.3101 | 1.4007 | 0.1380 | 0.0363 | 0.5838 | 2.247 | 102 | **0.027** |
| H5.1 | CALC(PERT,TOT) | -0.4051 | 2.4891 | 0.2453 | -0.8915 | 0.0814 | -1.652 | 102 | 0.102 |
| H5.2 | CALC(PSG,TOT) | -0.5483 | 2.2161 | 0.2184 | -0.9814 | -0.1152 | -2.511 | 102 | **0.014** |
| H5.3 | CALC(SRA,TOT) | 1.5707 | 2.0434 | 0.2013 | 1.1713 | 1.9700 | 7.801 | 102 | **0.000** |
| H5.4 | CALC(EVM,TOT) | 0.3708 | 1.7924 | 0.1766 | 0.0205 | 0.7211 | 2.100 | 102 | **0.038** |
| H6.1 | CRIT(PERT,TOT) | -0.5240 | 3.1889 | 0.3142 | -1.1472 | 0.0992 | -1.668 | 102 | 0.098 |
| H6.2 | CRIT(PSG,TOT) | -0.9560 | 2.5882 | 0.2550 | -1.4619 | -0.4502 | -3.749 | 102 | **0.000** |
| H6.3 | CRIT(SRA,TOT) | -0.8153 | 3.2717 | 0.3224 | -1.4547 | -0.1759 | -2.529 | 102 | **0.013** |
| H6.4 | CRIT(EVM,TOT) | 0.3911 | 2.2381 | 0.2205 | -0.0464 | 0.8285 | 1.773 | 102 | 0.079 |
| H7.1 | COMM(PERT,TOT) | -0.0968 | 2.2707 | 0.2237 | -0.5406 | 0.3470 | -0.433 | 102 | 0.666 |
| H7.2 | COMM(PSG,TOT) | -0.9560 | 2.5882 | 0.2550 | -1.4619 | -0.4502 | -3.749 | 102 | **0.000** |
| H7.3 | COMM(SRA,TOT) | -0.2837 | 2.3140 | 0.2280 | -0.7360 | 0.1685 | -1.244 | 102 | 0.216 |
| H7.4 | COMM(EVM,TOT) | 0.2106 | 1.7749 | 0.1749 | -0.1363 | 0.5575 | -1.204 | 102 | 0.231 |
| H8 | UNST(PERT,EVM) | 0.1327 | 3.8564 | 0.3800 | 0.8864 | -0.621 | -0.349 | 102 | 0.728 |
| H9 | ANLY(PERT,EVM) | 0.6056 | 3.3714 | 0.3219 | 1.2645 | -0.0533 | -1.823 | 102 | **0.071** |
| H10 | CREA(PERT,EVM) | -0.2403 | 3.4076 | 0.3358 | 0.4257 | -0.9063 | 0.716 | 102 | 0.476 |
| H11 | HOLI(PERT,EVM) | 0.5279 | 2.8261 | 0.2785 | 1.0802 | -0.0244 | -1.896 | 102 | **0.061** |
| H12 | CALC(PERT,EVM) | 0.7225 | 3.3150 | 0.3266 | 1.3704 | 0.0746 | -2.212 | 102 | **0.029** |
| H13 | CRIT(PERT,EVM) | 0.9151 | 3.8518 | 0.3795 | 1.6679 | 0.1623 | -2.411 | 102 | **0.018** |
| H14 | COMM(PERT,EVM) | -0.1197 | 3.2725 | 0.3225 | 0.5198 | -0.7593 | 0.371 | 102 | 0.711 |

Table 4 Details of the dataset

study PERT) but are better developed at the end of the course module (i.e., after solving the last case study EVM), it indicates that the case-based teaching approach in our course module helps developing skills for managing projects. Eq. (3) results in seven research hypotheses, i.e., one hypothesis for each skill x = {1, ..., 7}.

- H0: μx = 0: The null hypothesis assumes that the score for a particular skill x does not significantly improve along with the course module, and hence the score obtained after the last case study is similar to the score observed at the beginning of the course module.
- Ha: μx > 0: The alternative hypothesis assumes that there is a significant improvement in the score for a particular skill x along with the course module, which indicates that the case studies are a suitable technique for the development of skill x.

Note that this experiment does not measure the importance of skills (experiment 1) but rather the improvement of each skill throughout the course module, independent of their importance. In order to avoid confusion with the seven hypotheses of section 4.2, we refer in **table 6** to these new hypotheses as H8 to H14. Similar to the approach for experiment 1, we statistically test these hypotheses using a paired t-test. In this case, however, there exists an expected direction in the true mean difference of the alternative hypotheses Ha since we assume that the score for each skill will increase (and not decrease) between the start and the end of the course module. As a result, we consider a one-tailed paired t-test in this experiment (rather than a two-tailed paired t-test in the previous experiment).

### Results

The results are summarized in **table 6**. We observe that ANLY(PERT,EVM) (mean=0.61; p=0.071), HOLI(PERT,EVM) (mean=0.52; p=0.061), CALC(PERT,EVM) (mean=0.72; p=0.029) and CRIT(PERT,EVM) (mean=0.92; p=0.018) significantly improve between the first and last case study. The skill 'Understanding' (UNST(PERT,EVM)) does also improve, on average, throughout the course module (mean=0.13; p=0.728) but the improvement is not significant. The soft skills CREA(PERT,EVM) and COMM(PERT,EVM) seem to decrease along with the course module, however, this decrease is not significant since the null hypothesis (H0) cannot be rejected. The observation that certain skills do not improve during the course module might be due to the fact that there are only four sessions, which might be too short to observe an improvement in some skills. However, the fact that the ability to communicate does not improve is rather unexpected since the students solve the different case studies in a group. Given that the case studies should be solved under time pressure, each group of students needs to communicate intensively in order to successfully complete the course module. In summary, communication is important for the total score obtained in the course module (see section 4.2), but this skill does not seem to (significantly) improve throughout the course module. Good communication skills pay off, but they do not improve during the course module.

In conclusion, we observe that four out of the seven skills improve throughout the course module. This can be explained by the fact that knowledge and skills are transferred in our course module using a combination of lecturing sessions and case studies rather than a sole focus on standard classroom teaching. Furthermore, we show that both soft (Holistic and Criticality) and hard (Analysis and Calculus) skills improve throughout the course module, which is in line with many existing research studies that indicate the importance of both soft and hard skills in PM.

### Experiment 3: Validation of proposed model

In the previous experiments, we have investigated the importance of seven skills in four case studies and the improvement of these skills throughout the course module. However, these components have been investigated independently in the experiments. In experiment 3, we will investigate the impact of the different skills on the different case studies given that the case studies are interrelated according to the DS framework. More precisely, we present a model that integrates the skills, the case studies and the DS framework, and that is graphically shown in figure 3. In this model, the scores for the different case studies in the course module (PERT, PSG, SRA and EVM) are demonstrated by the scores for seven skills, and the score for one case study impacts the score of other case studies as discussed in the DS framework. We aim to validate this model by means of Structural

Equation Modeling (SEM), which is a well-established method for estimating complex models with latent variables and their relationship. In this research, we consider partial least squares SEM (PLS-SEM) that estimates parameters of a set of equations in a structural model by combining principal component analysis (PCA) with regression-based path analysis. The PLS-SEM method has been used in many disciplines such as operations management, information system management and supply chain management (Sarstedt, Ringle, and Hair 2017). A PLS-SEM model consists of constructs and indicators visualized as, respectively, circles and rectangles in **figure 3**. Constructs or latent variables are elements in the model that represent conceptual variables and are linked via single-headed arrows that represent predictive relations. Indicators or items are directly observed variables and are linked to their respective constructs. In our model, we observe four constructs (i.e., scores for the four case studies) and 28 indicators (i.e., seven skills per case study). A PLS-SEM model consists of two elements: a structural (inner) and a measurement (outer) model. The structural model represents the structural path between the constructs, while the measurement model represents the relations between each construct and the corresponding indicators. The model discussed in our research is a reflective model since the scores for the case studies are demonstrated by the skill levels rather than vice versa. In **figure 3**, this can be observed by the direction of the arcs between constructs and indicators: directed from the constructs (i.e., case studies) to the indicators (i.e., skills). In case that we would apply the PLS-SEM method to the model, including all skills for each case study, a singular matrix (i.e. a matrix without inverse) would occur during calculations possibly due to extreme collinearity between two or more skills. A detailed investigation showed that the following skills have a very high collinearity: {UNST(PSG),CREA(PSG),CRIT(PSG), COMM(PSG)} and {COMM(SRA),CREA(SRA)}. In order to resolve the

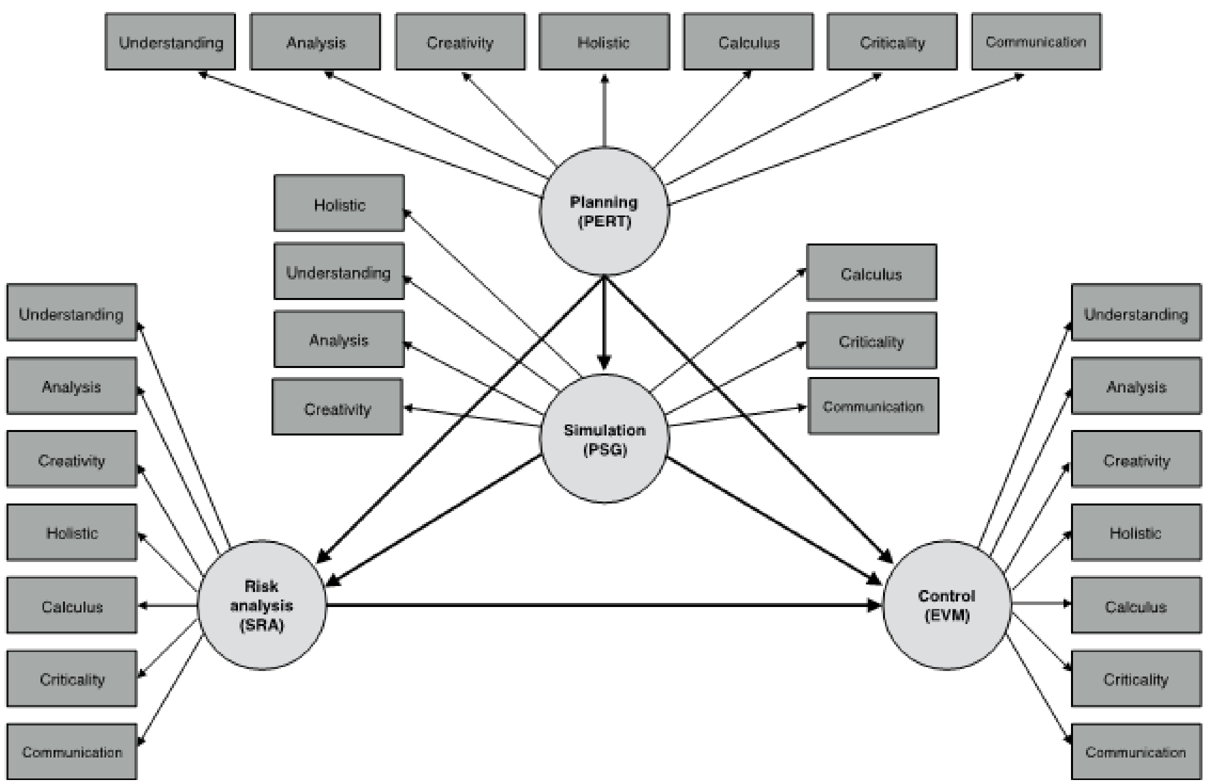


Figure 3 Structural and measurement model with all indicators





collinearity issue, we had to eliminate the understanding and criticality skill for the PSG case study (UNST(PSG),CRIT(PSG)) as well as the creativity skill for both the PSG and SRA case study (CREA(PSG),CREA(SRA)). The skills in bold (COMM(PSG) and COMM(SRA)) are the skills that were retained per case study.

## Approach

The PLS-SEM method provides loadings for each indicator in the outer model and path coefficients for the relations between the constructs in the outer model. Before we interpret and discuss the results of the PLS-SEM analysis, we will evaluate both the measurement and structural model in order to assure a high-quality PLS-SEM model.

The evaluation of the reflective **measurement model** consists of four steps: (1) indicator loadings, (2) internal consistency reliability, (3) convergent validity and (4) discriminant validity. First, we have to assess the indicator loadings (see **table 7**, column 'before elimination'). A loading above 0.7 shows a satisfactory degree of reliability as the construct explains more than 50% of the indicator's variance (Sarstedt, Ringle, and Hair 2017). In case that indicators have a loading lower than 0.7, they should be deleted from the model. A good practice is to eliminate the indicators one by one since the model changes and should be re-analysed each time an indicator is eliminated. The following indicators are eliminated in their respective order: UNST(PERT), COMM(PSG), ANLY(SRA) and HOLI(PERT). After these adjustments to the model, the indicator loadings are shown in **table 7** (column 'after elimination') and the resulting model is presented in **figure 4**. Secondly, we have to analyse the internal consistency reliability of the constructs. Researchers can analyse the Cronbach's alpha and the composite reliability, however, these measures are considered - respectively - a lower and upper bound on the internal consistency reliability. The reliability coefficient rho(A), which returns a value between both measures, can also be reported in PLS-SEM studies. The values for the different measures shown in **table 8** indicate that there is no problem (good values are indicated with * in table 8) with respect to the internal consistency reliability of all constructs. Thirdly, we should analyse the convergent validity by means of the average variance extracted (EVA) (see table 8). Since an acceptable threshold for the AVE is 0.5 (higher values are indicated with * in **table 8**), we can conclude that each construct explains the variance of the corresponding indicators in a satisfactory way. A final step is to assess the discriminant validity of the constructs in order to ensure that the constructs are sufficiently distinct from other constructs and how distinct the indicators represent only the corresponding construct. Discriminant validity assessment is analysed using the HTMT ratio of correlations with a suggested threshold value of 0.90 (see **table 8**). We can thus conclude that there is a high discriminant validity in the proposed model.

Given that the quality of the measurement model is validated, the assessment of the structural model is the next step in the PLS-SEM evaluation process. This step focuses on the predictive capabilities of the model and consists of three steps: (1) collinearity statistics, (2) coefficient of determination (R2) and (3) strength of path coefficients. In order to detect collinearity issues, the results of the variance inflation factor (VIF) analysis are shown in **table 7**, given that values above 5 are indicative of collinearity between the constructs (indicated with * in **table 7**). Secondly, the coefficient of determination (R2) values indicates the variance explained in each of the constructs.

The R2 (adjusted) values vary between 0.001 (-0.009) and 0.126 (0.108), which proves that the structural model is highly promising. Finally, the strength and significance of the path coefficients is evaluated. The path coefficients and corresponding p-values (between brackets) are indicated in figure 4 and we observe that two (three) path coefficients are significant at the 5% (10%) probability of error level. These two path coefficients show that project planning is an important point of reference for both

| | Loadings | | | | Loadings | | |
|---|---|---|---|---|---|---|---|
| | Before elimination | After elimination | Outer VIF | | Before elimination | After elimination | Outer VIF |
| UNST(PERT) | 0.260 | - | - | UNST(SRA) | 0.757 | 0.825 | 3.693* |
| ANLY(PERT) | 0.865 | 0.873 | 4.980* | ANLY(SRA) | 0.391 | - | - |
| CREA(PERT) | 0.766 | 0.769 | >20 | CREA(SRA) | - | - | - |
| HOLI(PERT) | 0.691 | - | - | HOLI(SRA) | 0.890 | 0.864 | 3.715* |
| CALC(PERT) | 0.898 | 0.924 | 7.894 | CALC(SRA) | 0.850 | 0.896 | 8.197 |
| CRIT(PERT) | 0.795 | 0.857 | >20 | CRIT(SRA) | 0.785 | 0.853 | 8.424 |
| COMM(PERT) | 0.925 | 0.966 | >20 | COMM(SRA) | 0.709 | 0.756 | 2.575* |
| UNST(PSG) | - | - | - | UNST(EVM) | 0.826 | 0.816 | 3.118* |
| ANLY(PSG) | 0.936 | 0.925 | 2,416* | ANLY(EVM) | 0.919 | 0.912 | 13.093 |
| CREA(PSG) | - | - | - | CREA(EVM) | 0.692 | 0.701 | 1.580* |
| HOLI(PSG) | 0.922 | 0.942 | 5.352 | HOLI(EVM) | 0.909 | 0.900 | >20 |
| CALC(PSG) | 0.868 | 0.881 | 4.115* | CALC(EVM) | 0.865 | 0.862 | 5.650 |
| CRIT(PSG) | - | - | - | CRIT(EVM) | 0.791 | 0.806 | 2.625* |
| COMM(PSG) | 0.336 | - | - | COMM(EVM) | 0.781 | 0.778 | 2.867* |

Table 7 Indicator loadings and collinearity statistics for experiment 3

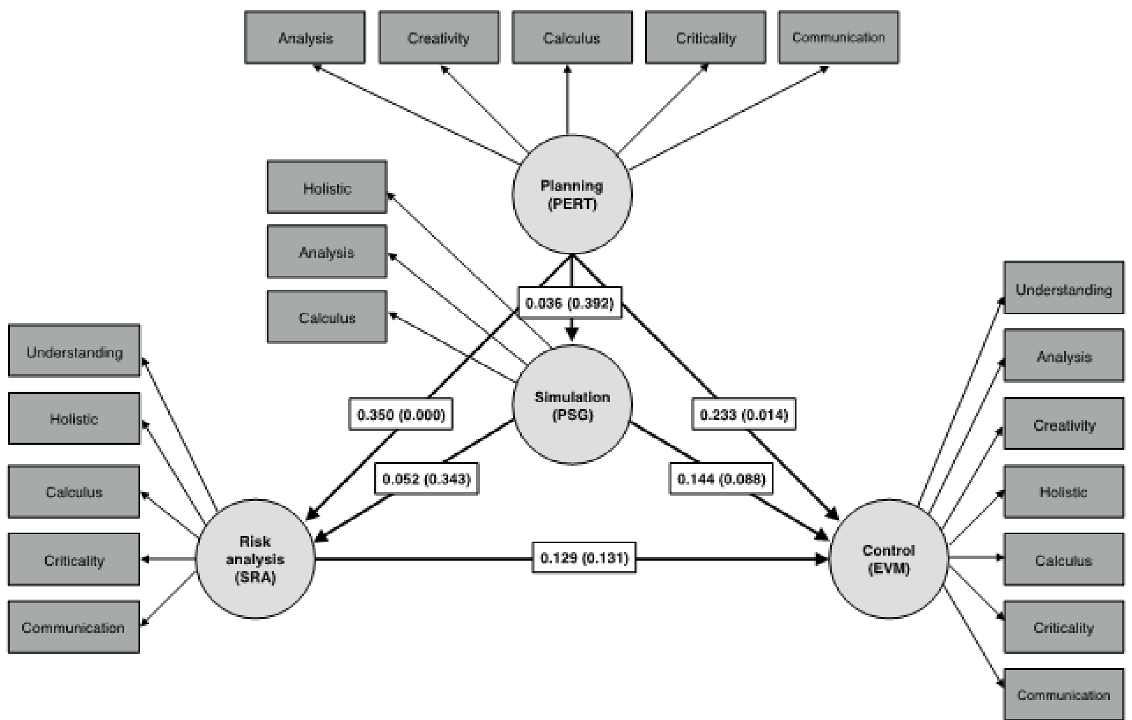


Figure 4 Structural and measurement model with reliable indicators

| Constructs | Construct reliability | | | | Discriminant validity | | | |
|---|---|---|---|---|---|---|---|---|
| | Cronbach's Alpha | Rho(A) | Composite Reliability | AVE | EVM | PSG | PERT | SRA |
| EVM | 0.923* | 0.932* | 0.938* | 0.685* | - | - | - | - |
| PSG | 0.910* | 1.001* | 0.940* | 0.839* | 0.154* | - | - | - |
| PERT | 0.926* | 0.934* | 0.945* | 0.775* | 0.277* | 0.076* | - | - |
| SRA | 0.901* | 0.997* | 0.923* | 0.706* | 0.206* | 0.069* | 0.338* | - |

Table 8 Construct reliability and discriminant validity for experiment 3





risk analysis and project control. Although that the PSG-EVM relation is significant at the 10% probability of error level, most of the relations of the PSG construct with other constructs in the model are not significant. Furthermore, we observe that R2 = 0.001 is the lowest R2 - value of all constructs and thus this is the construct that can be least supported in our model.

### Results

The above analysis shows that the quality of the structural as well as the measurement model is promising and results in the following main observations:

- 1. Since we have identified the set of skills for the complete course module rather than each case study individually, it might happen that some skills are highly correlated for certain case studies. Such skills, although very different, will measure the same performance in a specific case study. As a result, this analysis allows us to identify skills that are closely related and thus avoid considering two skills in a case study that measures the same performance. For example, we observe that the 'Communication' and 'Creativity' skill in the SRA case study are highly correlated. In this session, a set of proposals should be analysed and it is unclear whether the individual creativity or the communication between the students is essential for the analysis of these proposals.
- 2. The analysis indicates the skills that are reliable indicators for the performance in the different case studies. As a result, we are able to identify the specific skills that are relevant in each case study individually from a general set of seven skills that are important in the course module.
- 3. We observe that all seven skills are a reliable indicator for the performance in at least one case study. Also, each case study consists of a combination of soft and hard skills even after the exclusion of some unreliable skills in certain case studies.
- 4. The PSG construct has the lowest number of indicators since the performance during this case study is only reflected by the ability to analyse (ANLY), use analytical methods correctly (CALC) and present a holistic approach (HOLI). However, all seven skills are important to reflect the performance in the EVM construct. The PERT and SRA constructs are both reflected by five skills.
- 5. The results show that there exists a significant relation between the planning case study and the risk analysis case study as well as between the planning case study and the project control case study. These observations support a basic assumption in the DS framework: a good project schedule is an important point of reference for effective risk analysis and project control. Although risk analysis and project control are often suggested as key tools to obtain project success, they can only be effective when they are supported by a high-quality project schedule.

We conclude that our model to measure the performance of different case studies by means of a limited set of soft and hard skills can be validated.

## CONCLUSIONS AND FUTURE RESEARCH

Case-based PM education programs are considered a very effective way to improve soft and hard skills as well as teach new PM techniques and models. In this research, we present a Data-driven Project Management course module that consists of four sessions in which groups of students have to solve a set of complex case studies based on the DS framework: project scheduling (PERT), simulation game (PSG), risk analysis (SRA) and project control (EVM). Each session consists of two parts. In the first part, a theoretical introduction about the respective topic (PERT, PSG, SRA and EVM) is given by the lecturer in order to improve the knowledge of the students on this topic. In the second part, the students have to solve a case study after which they have to hand in a written report that summarizes their approach and results. Based on the data collected in nine programs over a three-year time period at two business schools, we are able to analyse the impact of PM skills on the performance during the course module as well as the development of these skills throughout the course module.

First of all, the results indicate that both soft and hard skills impact the performance of the students during the course module. Where the hard skills are mainly important at the start and end of the course module, the soft skills are important throughout the entire course module. The results show that the challenges and discussions in the PM process have a positive effect on the development of both soft and hard skills. Therefore, future PM education programs should use a case-based approach in order to develop both soft and hard skills. Secondly, we also observe that both the hard and soft skills improve throughout the course module. The final experiment shows promising results for both the structural and the measurement model using PLS-SEM. The structural model indicates that significant relations exist between the different case studies in the DS framework and confirms that project planning is an important point of reference for risk analysis and project control. However, the relations between the PSG case study and the other case studies in the DS framework are least supported in our experiments. The measurement model shows that not all seven skills are important in each case study, but at least a combination of soft and hard skills is key in each case study. The performance in the simulation case study is reflected by the lowest number of skills (Holistic, Analysis and Calculus), while all seven skills are significant for the project control case study. We observe that the ability to correctly use complex formulas is the only skill that is important for all case studies, which can be expected given the quantitative nature of the course module.

In the future, the following research efforts could be investigated. First of all, our study indicates that there exist significant relations between the case studies, however, a more detailed analysis could be conducted to validate the DS framework that supports our course module. More precisely, the relative strength of the relations between the different components of DS could be investigated. Although our course module is an intense process for the students, a second future research avenue is to duplicate this experiment in a course module with more contact hours over a longer period of time. This experiment could validate whether the limited improvement of certain (soft) skills can indeed be explained by the short timespan of the Data-driven project management course. Thirdly, we have mentioned in this manuscript that the set of (hard and soft) skills considered in this study is determined based on literature and our own assessment. Therefore, further research on the skills that impact the different aspects of project management and decision-making could contribute to future PM education programs.

## DECLARATION OF CONFLICTING INTEREST

The authors declare that there is no conflict of interest.

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