Biological Lifestyle Factors in Adult Distance Education

Predicting Cognitive and Learning Performance

Jérôme Gijselaers

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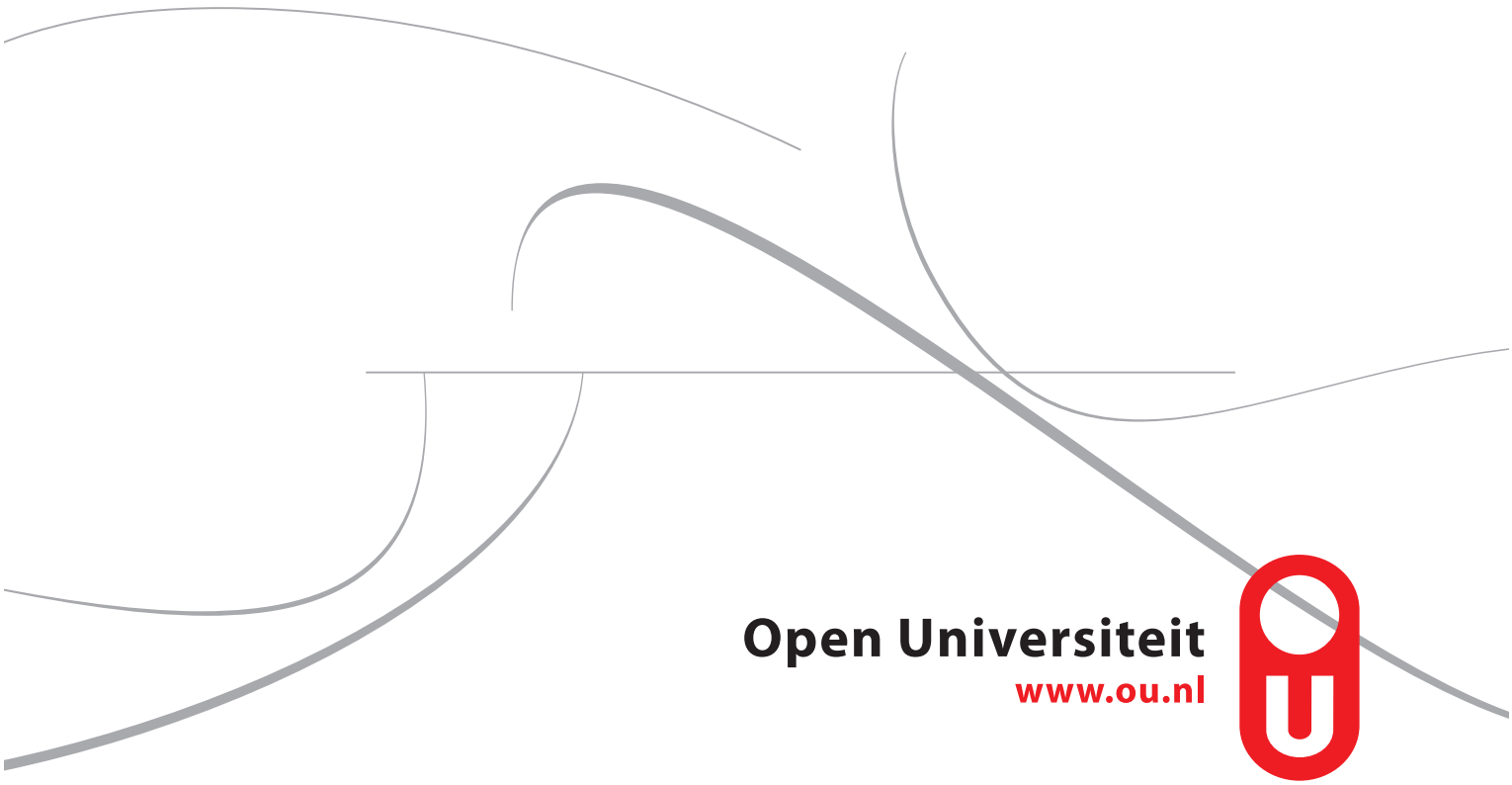

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Biological Lifestyle Factors in Adult Distance Education

Predicting Cognitive and Learning Performance

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aan de Open Universiteit
op gezag van de rector magnificus

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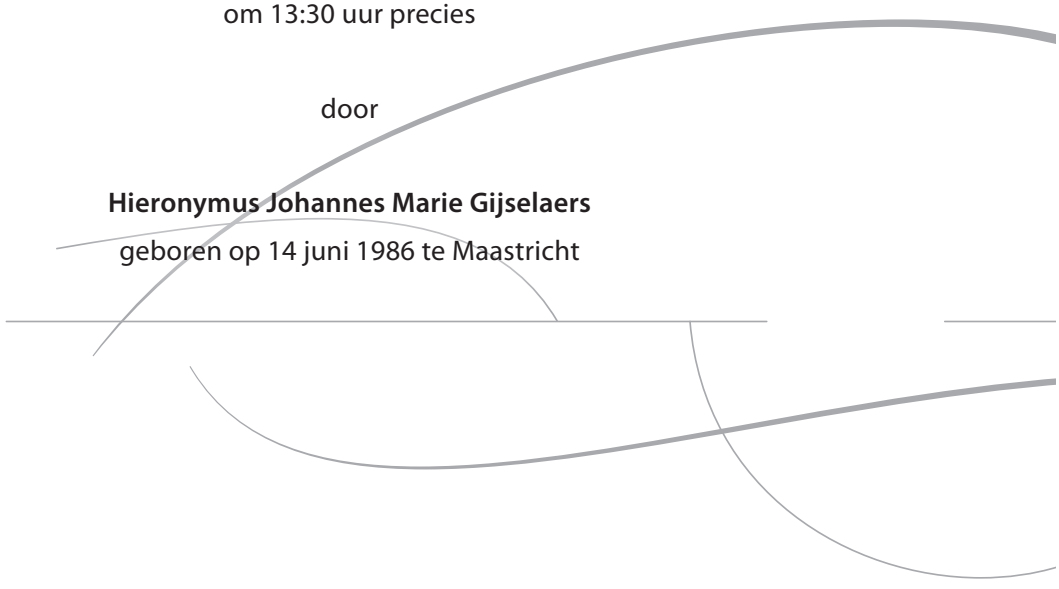

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Veur miene leeve pap

Er is maar één land: de aarde
Er is maar één volk: de mensheid
Er is maar één geloof: de liefde
(Dr. F.M. Wibaut)

PROLOOG

Het begon al toen ik klein was. Alles werd onderzocht en uit elkaar gehaald. Menig keukenwekker moest mijn moeder ten onder zien gaan aan mijn onderzoeksdrift. Eigenlijk was het toen al duidelijk dat ik wetenschapper werd. En zo begon ik – in augustus 2011 – aan mijn promotie-avontuur. Ondanks mijn zin en enthousiasme voor mijn nieuwe baan, was het door persoonlijke omstandigheden ook een moeizame start. Uiteindelijk vond alles langzaam weer een plek.

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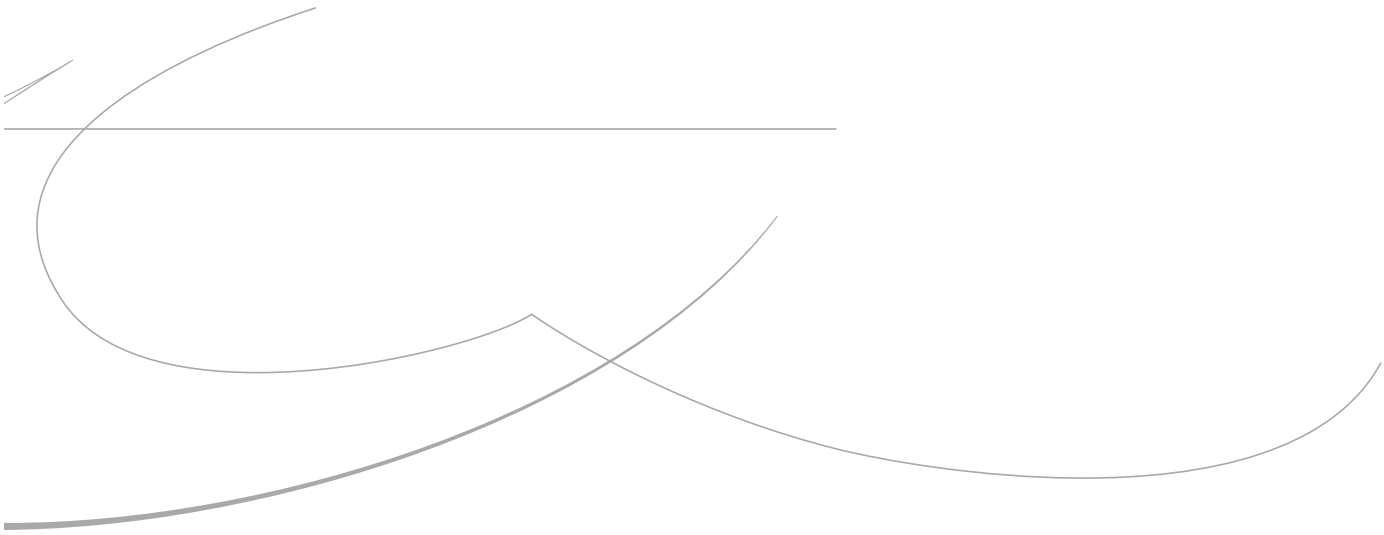
Jérôme, 21 september 2015

TABLE OF CONTENTS

Chapter 1	General introduction	1
Chapter 2	The Adult Learning Open University Determinants (ALOUD) study: Biological and psychological factors associated with learning performance in adult distance education	11
Chapter 3	Characteristics of successful, non-successful and non-starting students in adult distance education	25
Chapter 4	Physical activity and sedentary behavior do not predict study progress in adult distance education	41
Chapter 5	Chronotype, sleep quality and sleep duration in adult distance education: Not related to study progress	55
Chapter 6	The consumption of fish, caffeine and/or breakfast does not predict study progress in adult distance education	69
Chapter 7	Biological lifestyle factors related to cognitive performance: Sedentary behaviour predicts processing speed	85
Chapter 8	General discussion	111
Appendices		125
References		141
Summary		159
Samenvatting		165
ICO dissertation series		171



CHAPTER 1

General introduction

"Mens sana in corpore sano" not only Juvenal (~one century B.C.)
but also Plato (~four centuries B.C.) already held the belief
that a healthy body constitutes a healthy mind.
– Eat balanced, sleep well and be physically active –
This lifestyle will take care of a healthy body and brain.
But does this also translate in better learning?

Direct brain research (i.e., magnetic resonance imaging) shows that environmental factors play an important role in the development of the brain and its cognitive and learning capacities (Thompson et al., 2001). These environmental factors include many factors among which are physical activity, sleep and nutrition. These three factors, which are determined by lifestyle, have become of increasing interest recently. Research in traditional education found certain aspects of physical activity (e.g., active vs. passive behavior: Fedewa & Ahn, 2011; Tremblay et al., 2011), sleep (e.g., sleep duration and quality: Dewald, Meijer, Oort, Kerkhof, & Bögels, 2010) and nutrition (e.g., breakfast and poly-unsaturated fatty acids: Frensham, Bryan, & Parletta, 2012) to be associated with learning performance in children and adolescents. Such factors are called biological lifestyle factors (BLFs). There is no reason that these BLFs should not also influence learning performance in other educational settings. The goal of this dissertation is to investigate the relation between variables within the domain of these BLFs on the one hand and learning performance and cognitive performance on the other in a distance education (DE) setting. This investigation was executed within the Adult Learning Open University Determinants (ALOUD) study.

Relevance of distance education

DE is a form of continuing lifelong education primarily followed by adults. Learning in this population is important for a number of reasons. First, life expectancy is increasing and the fastest growing group is that of older adults (The Netherlands: Centraal Bureau voor de Statistiek, 2014; Worldwide: United Nations, 2012). Second, retirement age policies are being upwardly revised. Third, our knowledge-based economy is developing quickly. As a result of these three reasons, people have to work and learn longer. To accommodate the increasing need to continue to develop professional knowledge and experience far into adult age (Eurydice, 2011), people often participate in formal continuing education, in addition to informal learning (e.g., on the job/ workplace learning). This adult population generally has to combine family and work responsibilities with their study, which is why they often choose for DE. DE increasingly uses Information and Communication Technology allowing these students to study when and where they choose, often at a self-determined pace.

Definitions

In order to understand this dissertation, a number of commonly used terms first needs to be carefully defined. These terms are: distance education, learning performance and cognition.

Distance education

Schlosser and Simonson (2009) define DE as: "institution-based, formal education where the learning group is separated, and where interactive telecommunications systems are used to connect learners, resources, and instructors" (Schlosser & Simonson, 2009, p. 1). This definition is applicable to the most up-to-date types of DE, but not specifically to older forms of DE. The choice for this definition was made as this definition fits best with the type of DE under investigation in this dissertation. Four components are important in this definition. First, institution-based differentiates the education from informal and non-formal learning. Second, teacher and student are separated, often through geographical location, but also through time. Third, interactive telecommunications means the communication at distance, nowadays often via the Internet, but also via telephone. Fourth, resources are organized into actual learning experiences through instructional designs permitting learning (Schlosser & Simonson, 2009). Important to note here is that we use the term DE. However, the following terms are also often used to refer to DE: distance learning; online learning; online education; web-based learning; asynchronous learning; and e-learning.

The research reported on in the current dissertation is related to students of the Open University of the Netherlands. This formal university-level DE institution provides education following a modular structure. Students can register and start throughout the year as a result of this modular system and because there is no fixed curriculum. In addition, the education is self-paced[1]. The university is open to everyone, with the only restrictions that an age of at least 18 years old is obligatory and for entrance at the master level a bachelor diploma is necessary (and possible other requirements based upon the specific prerequisites per master). The Open University of the Netherlands mainly delivers online education.

The system of the Open University of the Netherlands brings great flexibility to the students on the one hand, but brings disadvantages to analyses regarding the goals of the ALOUD study on the other. Considering that every student can determine his or her own study path, learning performance can be difficult to operationalize and to interpret. In this dissertation, DE students are defined as students participating in DE delivered by a higher education institute and the students are characterized by having the adult age (i.e., 18 years or over, according to the Dutch law).

[1] The Open University of the Netherlands recently switched to a new educational model (i.e., this was implemented in phases from September 2015 onwards). This means the education is no longer self-paced and has a fixed curriculum.

Learning performance

Learning performance was chosen as the general umbrella term to indicate measures of performance in an educational setting. In traditional education the most common measures are academic achievement and school performance. These are often measured using Grade Point Average (GPA) or direct grades on examinations. In the DE provided by the Open University of the Netherlands it is, however, not useful to use GPA as a measure of learning performance considering that not all courses use a graded examination (i.e., they use pass or fail). This makes it impossible to compare students based on their grades. Learning performance was therefore operationalized in a different way. First, as student group (i.e., successful, non-successful and non-starting) to investigate the differences in these groups. Second, as study progress, to investigate the progress students made when they started studying. For student group, non-starters are students that during the initial subscription period (i.e., 14 months) did not attempt to officially finish a course. Non-successful students are those who did attempt to finish a course but were unsuccessful. Successful students successfully finished one or more courses.

Study progress was operationalized as the number of successfully completed modules after 14 months (i.e., the standard subscription period when registering for a course). A course at the Open University of the Netherlands consists of one or multiple modules. One module is equal to 4.3 European Credits (EC) in the European Credit Transfer System (ECTS). The nominal study load for one module is approximately 120 hours. Thus, using study progress as a measure of learning performance is a better representation than GPA as it is assumed that most modules are designed in accordance with the nominal number of hours.

Cognition

Cognition is a term that is often used to refer to the mental abilities that facilitate processes such as memory, planning, inhibition and problem solving. Cognition is a broad term that includes simple lower order processes such as processing speed, to more complex higher order processes such as mental set shifting. In the cognitive domain, the executive functions (EFs) are considered to be important for learning performance (Diamond, 2013). EFs are top down controlled mental processes that are needed for concentration and attention. The use of EFs take effort and not using them means: following automatic behaviour; not changing what you are doing; and giving in to temptations (Diamond, 2013). Three EFs are described in the literature, which are based on Baddeley's model of working memory (Baddeley, 1983) and his later proposal on the functions performed by the 'central executive' (Baddeley, 1996). Miyake and colleagues described these functions as inhibition, updating and shifting, after statistically analysing Baddeley's proposal (Miyake et al., 2000). More information regarding cognitive functions will be given in the respective chapters.

Relevance of this dissertation

Research in DE has mainly focused on changing the educational program to improve learning performance. However, the shift of perspective from educational program to the student has not yet been made. On the student level there is a number of factors possibly influencing learning performance. Next to the unchangeable genetic components that influence learning performance, environmental factors, among which biological lifestyle factors (BLFs), are fairly changeable parameters. Research in children and adolescents in traditional education shows that BLFs are an important contributor to learning performance. In DE, very limited research is available regarding BLFs and learning performance. Research into the relations between BLFs and learning performance could be an important addition to the field.

Via direct and indirect mechanisms affecting brain processes, these BLFs can influence learning (see the section 'Mechanisms' below). The physiological principles that are the basis of these influences belong to the field of neuroscience. As a result of knowledge in this area, there is a growing interest in and debate on the relation between cognitive neuroscience and education (Ansari & Coch, 2006). The connections between these two fields allow educators and cognitive neuroscientists to benefit from each other to gain new perspectives for posing and answering crucial questions about the learning brain. Most of this work focuses on implementing new neuroscientific insights in primary and secondary education (Goswami, 2006). However, the combination of these insights regarding DE is lacking. This multidisciplinary approach can provide new insights.

Physical activity, sleep and nutrition are BLFs that have consistently been shown to be related to learning performance in traditional education and in some cases also in DE. There is a clear overlap in the underlying physiological processes caused by behavior on the separate BLFs (Van Praag, 2009). Also here, a multidisciplinary approach can be pursued, meaning that the different fields of physical activity, sleep and nutrition can be brought together. Research on the combination of behavioral variables from each field is hardly available in traditional education and totally lacking in DE, when it concerns learning performance. Combining certain behaviors within these separate domains can possibly amplify or attenuate certain processes as a result of synergistic or interactive effects, respectively. This dissertation is a unique, new and multidisciplinary research study that tries to elaborate on the relation between the BLFs and learning performance.

Biological lifestyle factors

A short description of all the BLFs will be given. In the respective chapters, subsequent operationalization of the specific variables and argumentation for choosing them will be given. There are three biological factors included in the research reported in this dissertation: physical activity, sleep and nutrition.

Physical activity is defined as bodily movement produced by skeletal muscles that requires substantial energy expenditure (Barenberg, Berse, & Dutke, 2011). Physical

activity itself implies the activity of a person during the day. It is not only the time spent on physical activities, but also the intensity with which activities are executed. The flip side of physical activity is sedentary behavior. Sedentary behavior can actually be seen as physically inactive. However, recently it is more and more viewed as an independent construct (Rhodes, Mark, & Temmel, 2012). For this reason sedentary behavior is included as a separate measure. In traditional education, physical activity (Fedewa & Ahn, 2011) and sedentary behavior (Tremblay et al., 2011) were found to be associated with learning performance in children and adolescents.

Sleep is defined as a reversible state of reduced responsiveness, usually accompanied by immobility (Cirelli & Tononi, 2008). In this dissertation, the investigated measures related to sleep are chronotype (i.e., time of day preference), sleep quality and sleep duration. Sleep research has provided knowledge that there are individual differences among people in circadian rhythms. The circadian rhythm determines a number of physiological processes (e.g., blood pressure and hormone secretion) and hence the alertness of people differs throughout the day, which can influence learning performance. Chronotype is the preference one has in this circadian rhythm, meaning, whether one is more a morning person or an evening person. Sleep duration and sleep quality are two separate constructs that overlap to some extent. Self-reported sleep quality is a more subjective measurement of how someone evaluated the night's sleep and how rested one feels in the morning. Sleep duration, on the other hand, is a more objective construct based on the reported sleep and wake time of a person (Pilcher, Ginter, & Sadowsky, 1997). In traditional education, chronotype (Boschloo et al., 2012; Randler & Frech, 2009), sleep duration (Dewald et al., 2010) and sleep quality (Dewald et al., 2010) were found to be associated with learning performance in children and adolescents.

Nutrition is the domain describing food that contributes to health and growth, but also cognition. In this dissertation, the investigated measures related to nutrition are the consumption of caffeine, fish and breakfast. Depending on the way it is used, caffeine can be viewed as a nutrient, a drug or a drug of abuse (Pardo Lozano, Alvarez García, Barral Tafalla, & Farré Albaladejo, 2007). In this dissertation, caffeine will be regarded a nutrient as habitual caffeine use is investigated in a healthy adult population. Caffeine is a stimulant that seems to boost a variety of cognitive functions. Research shows that habitual caffeine intake is related to better long-term memory (Hameleers et al., 2000), alertness (Owen, Parnell, De Bruin, & Rycroft, 2008), reaction time and short term recall (Ruxton, 2008). The consumption of fish is a proxy measure for omega-3 long chain polyunsaturated fatty acids (n-3 LCPUFAs) plasma phospholipid levels (De Groot, Van Boxtel, Schiepers, Hornstra, & Jolles, 2009), which is thought to have implications on cell membrane composition and neurotrophins (Gómez-Pinilla, 2008; Van Praag, 2009), possibly translating into enhanced learning performance. Breakfast consumption is a heavily investigated nutritional measure in traditional education (Rampersaud, Pereira, Girard, Adams, & Metzl, 2005). Breakfast is an often skipped meal (Mullan & Singh, 2010) and is mostly considered as having

direct effects on cognitive performance as it gives the body energy after a night of fasting. In addition to providing direct cognitive benefits after consumption, breakfast can also be viewed as providing long term benefits as a result of more adequate whole diet nutrient intake, leading to a better nutritional status (Pollitt & Mathews, 1998), which could translate into better learning performance.

Mechanisms

There are many mechanisms responsible for the effects of BLFs on the brain and its performance. In the following chapters, mechanisms relevant to specific factors will be discussed with respect to how they influence certain physiological parameters that affect brain processes. These effects can be either very specific or very broad, in terms of the range of the effects. As an illustration, the effects of these physiological influences are generally related to:

- fuel delivery (e.g., glucose), a basic need for neurons to function;
- neurogenesis, the process of neuron creation;
- synaptic plasticity, the process of strengthening or weakening synaptic bonds;
- hormones, a signaling molecule to regulate physiology and behavior;
- spine density, the increase in the occurrence of possible synaptic locations;
- angiogenesis, the process of creating new blood vessels from other vessels;
- vascular growth factors, factors that enhance blood vessel growth;
- neurotransmitters, endogenous molecules that regulate signal transduction;
- neurotrophins, proteins that promote development, function and survival of neurons;
- cell membranes, providing proper permeability and fluidity important for signal transduction.

The processes relevant for *physical activity* are fuel delivery (Sünram-Lea, Foster, Durlach, & Perez, 2001), neurogenesis, synaptic plasticity, spine density, angiogenesis and vascular growth factors (Van Praag, 2009), neurotransmitters (Barenberg et al., 2011) and neurotrophins (Barenberg et al., 2011; Winter et al., 2007). For *sleep* these are hormones (Wright et al., 2013) and neurotransmitters (Diekelmann & Born, 2010). For *nutrition* these are neurotransmitters (Nehlig, Daval, & Debry, 1992), neurotrophins (Van Praag, 2009) and cell membranes (Gómez-Pinilla, 2008). Important to note is, that these processes summarized here do not need to be exclusive for that BLF, as this enumeration is not exhaustive. These physiological changes ultimately result in an increase in brain plasticity (Gómez-Pinilla, 2008; Kaliman et al., 2011), a benefit for learning.

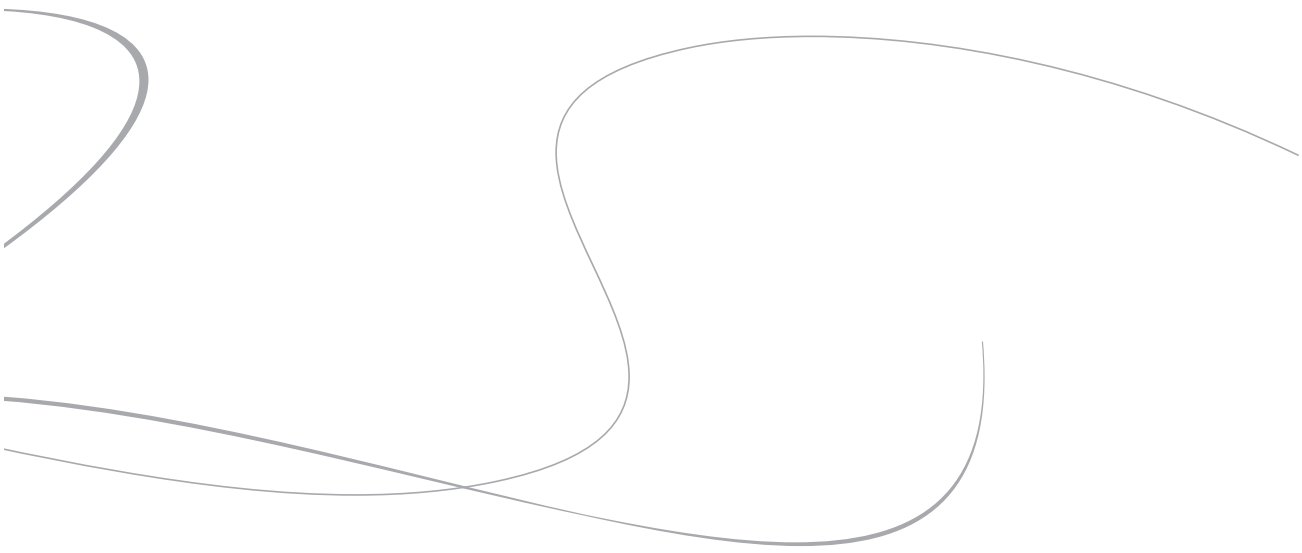
Aim of this dissertation

The aim of this dissertation was first to investigate the characteristics of different student groups (i.e., successful, non-successful, and non-starting). The second aim was to investigate whether BLFs predicted study progress in adults participating in DE.

Third, it was investigated whether the BLFs predicted cognitive performance, as it can be a predictor for learning. Last, the aim was to investigate whether a possible relation between the BLFs and learning performance was mediated by EFs.

Overview of this dissertation

This dissertation consists of nine chapters. *Chapter 2* provides an overview of the design of the full ALOUD study with all variables measured, the participants and the availability of the data. It is based on a published data paper and provides a description of the full ALOUD study. In the ALOUD study the relation between BLFs and psychological factors on the one hand are investigated in relation to learning performance on the other. This dissertation only focuses on BLFs in relation to learning performance. The relation between psychological factors and learning performance is not the focus of the current dissertation. *Chapter 3* provides the descriptives of participants of the ALOUD study with regard to study success. Three groups of students were formed and descriptive statistics are presented with regard to each group. Possible differences between groups were statistically tested for significance and reported. This chapter provides more insight in the differences between successful students, non-successful students and non-starting students. Next, the predictive value of physical activity, sleep and nutrition regarding study progress is reported in *chapter 4, 5 and 6*, respectively. The field of physical activity, sleep and nutrition are each separately large fields of science. The analysis of each BLF requires a thorough literature review beforehand. Each chapter extensively reviews the literature regarding the BLF that is investigated in relation to learning performance. This is first done within the field of DE. However, considering the scarcity of literature regarding DE, also literature regarding traditional education is reviewed. In addition, to complete the view on possible relations regarding learning performance, also literature regarding cognitive performance in adults was considered in case needed. This way, via deduction, hypotheses could be formed when considering the literature and the specific characteristics adult DE students have. *Chapter 7* gives an overview of the path analytic approach in which cognitive performance was predicted via the three BLFs. This specific study was part of an abroad research internship lasting three months at the Universitat Oberta de Catalunya in Barcelona in Spain. During this internship, the expertise of the statistical technique *structural equation modeling* was acquired and this specific chapter was the result. Three path models were built for each BLF after which they were integrated in one final model that was validated using a cross validation approach. Ultimately, *chapter 8* provides a short summary of the findings in each chapter and concluded with an integrative synthesis of the complete research execute in this dissertation. Limitations regarding methodology and suggestions for future research are given here.



CHAPTER 2

The Adult Learning Open University Determinants (ALOUD) study: Biological and psychological factors associated with learning performance in adult distance education

Learning is crucial for everyone. The association between biological (e.g., sleep, nutrition) and psychological factors (e.g., test anxiety, goal orientation) and learning performance has been well established for children, adolescents and college students in traditional education. Evidence for these associations for adult distance students is lacking however. The Adult Learning Open University Determinants (ALOUD) study is the first to identify the determinants of learning performance within adult distance education. Over the course of 1 year, all new students (n = 4945) of the Open University of the Netherlands were approached. At baseline, 2040 students fully participated in this observational longitudinal study by filling out an online questionnaire and performing cognitive tests. At the 7 and 14 months follow-up, participants filled out a second and third questionnaire respectively, and data were given by the exam registration office to measure learning performance at these times. The ALOUD study might result in tailor-made educational innovations for adults participating in distance education and, finally, a more successful distance education student population.

This chapter was based on: Neroni, J., Gijselaers, H. J. M., Kirschner, P. A., & De Groot, R. H. M. (2015). The Adult Learning Open University Determinants (ALOUD) study: Biological and psychological factors associated with learning performance in adult distance education. *British Journal of Educational Technology, 46*, 953–960. http://doi.org/10.1111/bjet.12288

Introduction

Learning is crucial for people of all ages. Though much is known about biological and psychological determinants of learning for children, adolescents and college students within traditional education, relatively little is known about determinants of learning performance of adults in distance education. This apparent lack of knowledge is the basis of the Adult Learning Open University Determinants (ALOUD) study.

Learning has been an area of interest for many researchers. Within children, adolescents and college students, the association between biological and psychological factors on the one hand and learning performance on the other has already been extensively studied (e.g., Howie & Pate, 2012; Richardson, Abraham, & Bond, 2012; Wigfield & Cambria, 2010). Although studies are mainly focused on the young, learning is not solely carried out by children; it is a process that is actively sought out by people of all ages.

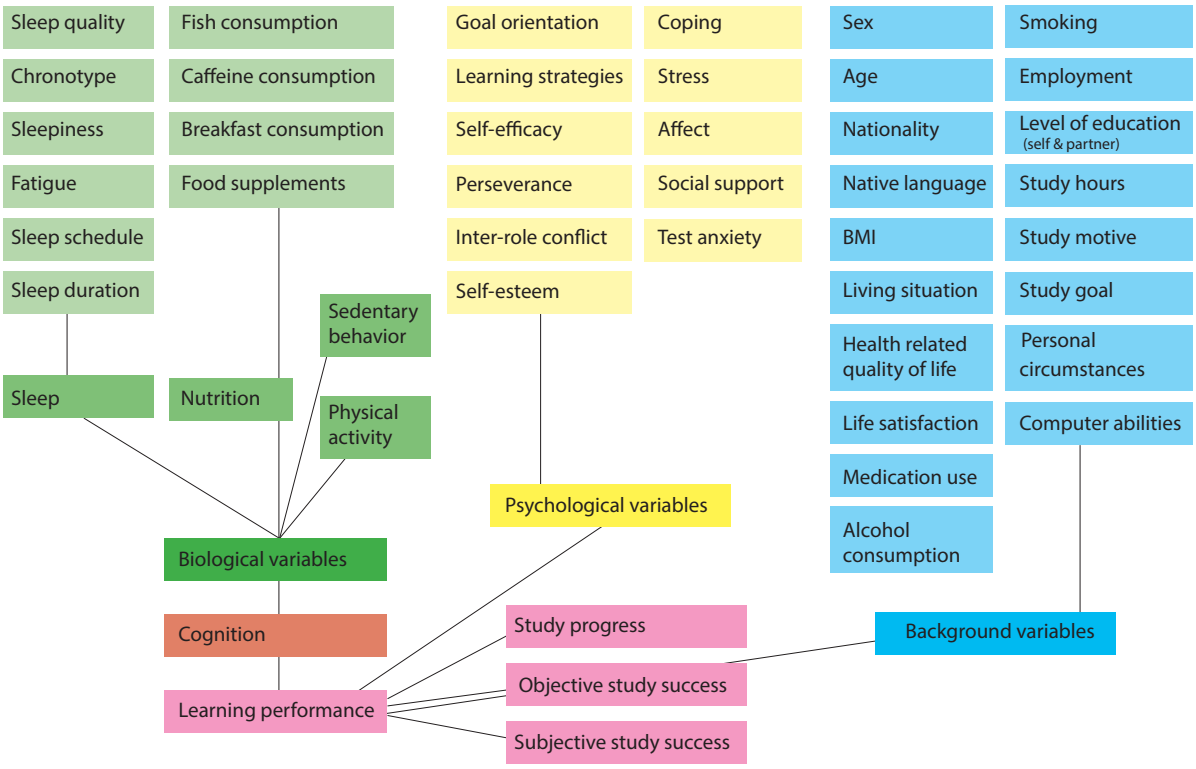


FIGURE 1. Visual overview of the ALOUD study.

In adult education, a field that is expanding in both importance as well as prevalence, it is not clear how these factors are associated with learning performance. This population is not only unique on the age dimension, but also with respect to the time factor. In this age category, people often try to combine jobs, families and hobbies, which in turn affects both the available time for study and their biological and psychological states.

ALOUD is the first study to identify the biological and psychological determinants of learning performance within adult distance education (see Figure 1). It will yield new insights in determinants for learning in lifelong perspective and in the change in time within the individual. Based upon the results from this observational study, effective innovations can be developed to optimize current learning programs. This will result in tailor-made lifelong learning programs.

Research method

Design

The study is an observational longitudinal study in adult distance students of the Open University of the Netherlands (OUNL) using an online questionnaire and cognitive tests.

Context

OUNL has seven educational bachelor and master programs: law, management sciences, computer sciences, environmental sciences, cultural sciences, educational sciences and psychology, which together contain approximately 300 different courses. No prior education is required to study at the OUNL (ie, open admission). The only requirement is a minimum age of 18 years. Students can be enrolled in one or more individual courses at once, or in a full-length degree program. They can choose from nearly 300 courses. In most courses, Dutch is the primary language, in some courses English. A course consists of one or more modules, and each module stands for 4.3 European Credits (ECs): 120 hours of studying. Students can begin a course any time they want and they can study at their own pace. Each course ends with an examination, which can be a written examination with open and/or closed questions, a computer based examination, an oral examination or a final project or paper. In general, students have three attempts to pass for an exam and they have to finish the course within 14 months from the time they started the course. Some courses have exams on fixed dates, whereas in other courses the student determines the date of the exam.

Procedure

Baseline

Students who signed up for their first course(s) at the OUNL between August 6, 2012 and August 5, 2013 automatically received an email invitation 14–21 days after successful registration. Before they were able to start with the questionnaire, participants were obliged to tick a box in order to agree to an informed consent form. At the end of the questionnaire, there was a link to three cognitive tests. In total, completion took 45–60 minutes. Participants were able to pause and return to the questionnaire at their choice.

Non-respondents and non-completers received an email reminder after 2 weeks. This was followed by a final reminder one more week later. Finally, individuals who had not completed the questionnaire or simply not responded to the mail were approached by phone 1 week after this last email.

First follow-up

After 7 months, students who fully participated at baseline were invited by email to participate in a short follow-up questionnaire consisting of two short questions. Non-respondents and non-completers received an email with a reminder after 2 weeks. Learning performance after 7 months was determined by collecting data from the exam registration office.

Second follow-up

After 14 months, students who fully participated at baseline were approached again via email to participate in the second follow-up questionnaire. Again, an email reminder was sent after 2 weeks in case of non-response or non-completion and a phone call was made 1 week later if necessary. This time, participants only filled out an online questionnaire, which took 30–60 minutes of their time. Again, participants were able to pause and return to the questionnaire at another chosen time. Learning performance after 14 months was determined by collecting data from the exam registration office. A time frame of 14 months was chosen, as students have 14 months to finish their course. After these 14 months, their course rights will expire and they have to pay extra to be able to finish the course.

Participants

Of the 4945 students who were approached, 2842 responded and 2040 (1260 women, 780 men, M_{age} = 36.7 years, age range: 18–80 years) fully participated at baseline (41.3% response rate). At the first follow–up, 1086 students completed the questionnaire (53.2% response rate). At the second follow-up, 1195 students completed the questionnaire (58.6% response rate).

Measurements

All original English items were translated from English into Dutch by a native Dutch speaker. To ensure the validity, these items were back-translated by a bilingual English/Dutch-speaking person. Adjustments were made where necessary.

Outcome variables

Learning performance

To compute learning performance, study progress information was gathered via the exam registration database of the OUNL after 14 months of studying. This data set consists of information on the course(s) the students are registered for. For each

course, the start and end date, the obtained number of ECs, the obtained grades and the number of attempts of exams are known. The richness of this study progress information offers the possibility to compute various outcome variables (e.g., learning performance, dropout, student success).

Subjective study success

At baseline, students were asked to indicate their main motive to start a course at the OUNL. They could choose out of seven motives (e.g., "I want to better fulfill my current working position"; "I want to develop my [intellectual] capacities") or give an open answer by choosing "other, namely . . ." At second follow-up, students were asked to what extent they achieved this goal and in the case they did not completely achieve it, if they still had the intention to achieve it.

Biological variables

Sleep

Different aspects of sleep were investigated: sleep quality, chronotype (ie, whether someone has a morning or evening preference), sleep duration, sleep schedule, sleepiness and fatigue.

Sleep quality. The quality of sleep was measured with the Pittsburgh Sleep Quality Index (PSQI; Buysse, Reynolds, Monk, Berman, & Kupfer, 1989), which measures seven different categories regarding sleep quality.

Chronotype. Chronotype was measured using the Munich ChronoType Questionnaire (MCTQ; Roenneberg, Wirz-Justice, & Merrow, 2003). It measures quantitative chronotype via reported sleep and wake times, and qualitative chronotype by one item rated on a scale ranging from *extreme morning type* (1) to *extreme evening type* (7).

Sleep duration. To measure sleep duration, items of the PSQI (Buysse et al, 1989) and items of the MCTQ (Roenneberg et al, 2003) were used.

Sleep schedule. Sleep schedule can be derived from items of the PSQI (Buysse *et al*, 1989) and MCTQ (Roenneberg *et al*, 2003) regarding sleep and wake times.

Sleepiness. Sleepiness was measured with the Epworth Sleepiness Scale (Johns, 1991), which estimates the chance to doze off or fall asleep during eight situations. Items were rated on a scale ranging from *I would never fall asleep* (1) to big *chance to fall asleep* (4).

Fatigue. To measure fatigue, the Fatigue Assessment Scale (Michielsen, De Vries & Van Heck, 2003) was used. Items were rated on a scale ranging from *never* (1) to *always* (5).

Nutrition

Different aspects of nutrition were measured: consumption of fish, caffeine, breakfast and supplements.

Fish consumption. Fish consumption was estimated by a validated short frequency scale (De Groot, Van Boxtel, Schiepers, Hornstra, & Jolles, 2009) on how often they ate three different categories of fish based on content of docosahexaenoic acid. Items were rated on a scale ranging from *never* (1) to *more than once a week* (5).

Caffeine consumption. To measure caffeine consumption, participants were asked if and how much coffee, black and green tea, and caffeine-containing energy drinks they consumed during an average day. Items were rated on a scale ranging from l*ess than one cup a day* (1) to *five or more cups a day* (6) for coffee and tea, and *less than one can (240 ml) per day* (1) to *five or more cans per day* (6) for caffeine-containing energy drinks.

Breakfast consumption. To measure breakfast consumption and composition, participants were asked how many days per week they had breakfast, if they had breakfast during working days and nonworking days (rated on a scale ranging from *never* [1] to *always* [5]) and what types of breakfast they consumed.

Food supplements. To measure food supplements intake, participants were asked whether they used supplements, and if so, what kind, brand, dose per pill and number of pills they used.

Physical activity

Different aspects of physical activity were measured: physical activity and sedentary behavior.

Physical activity. Physical activity was measured with the Short Questionnaire to Assess Health enhancing physical activity (SQUASH; Wendel-Vos, Schuit, Saris, & Kromhout, 2003). Physical activity was measured as the accumulated product score of intensity of the activity multiplied by the minutes spent on the activity.

Sedentary behavior. To measure sedentary behavior, a questionnaire based on the SQUASH (Wendel-Vos *et al*, 2003) was developed. Sedentary behavior was calculated by accumulating the minutes of sitting, sleeping and lying per week.

Psychological variables

Goal orientation

Goal orientation was measured with the Achievement Goal Questionnaire (Elliot & McGregor, 2001). This instrument consists of four subscales (mastery approach, mastery avoidance, performance approach and performance avoidance) with three items each. Additionally, work avoidance orientation was measured with the work avoidance subscale (three items) of a questionnaire developed by Harackiewicz, Durik, Barron, Linnenbrink-Garcia, and Tauer (2008). Items were rated on a scale ranging from *totally disagree* (1) to *totally agree* (7).

Learning strategies

To measure learning strategies, part B of the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, Smith, Garcia, & McKeachie, 1993) was used. This instrument consists of nine subscales: rehearsal (4 items), elaboration (6 items), organization (4 items), critical thinking (5 items), metacognitive self-regulation (12 items), time and study environment management (8 items), effort regulation (4 items), peer learning (3 items) and help seeking (4 items). Items were rated on a scale ranging from *totally disagree* (1) to *totally agree* (7).

Self-efficacy

Self-efficacy was measured with Self-Efficacy for Learning and Performance, a subscale of part A of the MSLQ (Pintrich *et al*, 1993). These eight items were rated on a scale ranging from *totally disagree* (1) to *totally agree* (7).

Perseverance

To measure perseverance, participants filled out the Grit Scale (Duckworth, Peterson, Matthews, & Kelly, 2007). This scale comprised 12 items rated on a scale ranging from *totally disagree* (1) to *totally agree* (5).

Inter-role conflict

Inter-role conflict was measured by using the Work-Family-School Conflict Survey (Kohler Giancola, Grawitch, & Borchert, 2009). This questionnaire included 14 items rated on a scale ranging from *totally disagree* (1) to *totally agree* (5) in two areas: Family-School Conflict (7 items) and Work-School Conflict (7 items).

Self esteem

Rosenberg's Self-Esteem Scale was used to measure self-esteem (Rosenberg, 1965). It comprised 10 items rated on a scale from *totally disagree* (1) to *totally agree* (4) items.

Coping

To measure coping, the Utrechtse Coping Lijst (Schreurs, Van de Willige, Brosschot, Tellegen, & Graus, 1993) was used. Participants responded to this 47-item questionnaire on a scale ranging from *rarely* or *not at all* (1) to v*ery often* (4). It consists of seven subscales, namely: active tackling (seven items), palliative reacting (eight items), avoiding (eight items), seeking social support (six items), passive reacting (seven items), expression of emotions (three items) and reassuring thoughts (five items).

Stress

Participants were asked to indicate whether they had experienced stressful events during the previous year. This could both be positive (e.g., pregnancy, marriage) as well as negative (e.g., losing job, divorce) events. For each stressful (max. 5) event they had experienced, they were asked to name what the event was (open answer) and how stressed they had felt lately because of the event on a scale ranging from *rarely* or *not at all* (1) to *very much* (5). They were then asked to indicate how stressed they currently felt on the same 5-point scale.

Affect

Positive and negative affect was measured with the Positive and Negative Affect Schedule (Watson, Clark, & Tellegen, 1988). Participants were asked to indicate how they have felt in general in relation to 10 positive (e.g., enthusiastic, inspired) and

10 negative (e.g., afraid, hostile) emotions and feelings. Items were rated on a scale ranging from rarely or *not at all* (1) to *very much* (5).

Social support

Three types of social support were measured: financial, mental and practical social support. For each type, participants were asked to indicate how much support they received from one's social circle (ie, spouse, other family members, employer, colleagues, friends, university employers [e.g., study coach] and peer students). Items were rated on a scale ranging from *not at all* (1) to *very much* (5).

Test anxiety

To measure test anxiety, the five-item test anxiety subscale of the MSLQ (Pintrich *et al*, 1993) was used. Items were rated on a scale ranging from *totally disagree* (1) to *totally agree* (7).

Cognitive performance

To measure cognitive performance, participants were asked to complete three digitized cognitive tests: (1) the Trail Making Test (Army Individual Test Battery, 1944) as a measurement for shifting; (2) the Substitution Test (Smith, 1991) as a measurement for information processing speed; and (3) the N-back task (Lezak, Howieson, & Loring, 2004) as a measurement for working memory and updating. Additionally, reaction times were recorded for all tests, which provide extra information about speed.

Background variables

Sex

Sex was measured as there are profound sex differences in intelligence (e.g., on the domains of memory, reasoning and science) which could influence study progress. There are intellectual domains where males excel females (e.g., spatial reasoning) and vice versa (e.g., verbal fluency; Halpern, 1997).

Age

Age was measured, via date of birth, as memory performance declines with increasing age (Grady & Craik, 2000), possibly hampering learning efficiency.

Nationality

Investigated as Dutch or other, with a possibility to fill in, as non-Dutch nationals could have more difficulties with the language.

Native language

Native language as Dutch or other, with a possibility to fill in, as non-Dutch speakers could have more difficulties with the language.

Body mass index

Body mass index (computed from weight and height), as it is negatively associated with learning performance (Crosnoe & Muller, 2004).

Living situation

Within living situation multiple parts were measured: first, the living situation of the participant (e.g., living alone, living with partner, living with partner and children, living with parents, etc.) as social support gained from immediate surroundings is a key element in successful learning (Crean, 2004), living situation is an important variable to take into account. Second, also the number of children living at home was asked (i.e., if applicable), as this could possibly provide distractions from learning.

Health related quality of life

Health related quality of life was investigated using the RAND-36, a questionnaire providing 9 scale scores on: physical functioning; social functioning; physical role limit; emotional role limit; mental health; vitality; pain; general health perception; and health change (i.e., over the last year) (Van Der Zee & Sanderman, 1993), as health problems could prohibit learning.

Life satisfaction

Life satisfaction was investigated using the satisfaction with life scale (Diener, Emmons, Larsen, & Griffin, 1985), as more satisfaction is synergistic with better learning (Seligman, Ernst, Gillham, Reivich, & Linkins, 2009).

Medication use

Medication use was measured to investigate medication side effects, as the use of certain medication can have implications on the learning capacity. Each individually reported medicament was manually scored by its possible side effects.

Alcohol consumption

Alcohol consumption (in standard glasses per week) was measured as it has been found to influence study progress (Singleton & Wolfson, 2009).

Smoking

Smoking (whether someone smokes or not) was measured as the use of tobacco has negative implications on cognition (Caspers, Arndt, Yucuis, McKirgan, & Spinks, 2010; Fried, Watkinson, & Gray, 2006; Kalmijn, Van Boxtel, Verschuren, Jolles, & Launer, 2002), which could translate into impaired learning.

Employment

Within employment, multiple parts were measured: first, type of work contract, whether someone works part time, full time or not at all. One would expect that

students with more job commitments would perform less. However, it has been found that workers with less than 20 work hours per week perform worse than their counterparts working more (Taplin & Jegede, 2001), making it important to review this characteristic. Second, regularity of work times, as it has been shown that low achievers are more likely to have irregular work times (Taplin & Jegede, 2001). Third, number of working hours per week, as common sense and literature (Eppler & Harju, 1997) suggests that more working hours lead to less study progress, as less study time is remaining. However, as indicated above, this is not necessarily the case (Taplin & Jegede, 2001).

Level of education

Two items were measured: first, level of previous education of the participant (ordinal variable with eight levels following De Bie (1987), as previous level of education has been found to be a significant predictor of academic success for students (Bernt & Bugbee, 1993). Second, level of previous education of the partner (if applicable) (De Bie, 1987), as this highly correlates with the level of education of the participant under investigation (Kalmijn, 1998; Komter, Keizer, & Dykstra, 2012);

Study hours

Expected average number of study hours per week to be invested (as reported by the students) was measured as more time invested is likely to lead to better results (Bernt & Bugbee, 1993).

Study motive

It was measured whether the study motive was personal or professional, as intrinsic motivation is a better motivator for learning than external triggers (Ryan & Deci, 2000).

Study goal

To items were measured: first, a general goal for studying (i.e., one or more courses, short study program, bachelor degree, master degree, premaster, orientation, no specific goal), the main intention of students to start studying (e.g., orientation or an entire bachelor degree), as this indicates the intention to succeed. Second, a specific study goal (expected number of completed modules after 6 months) as it provides a clear estimation of the expectation and hence the intention of the study progress to be made.

Personal circumstances

It was investigated whether participants had a learning restriction, as certain restrictions (i.e., officially recognized psychological problems or learning disorders) can impose problems regarding the learning process.

Computer abilities

Computer abilities were measured via a self-developed questionnaire mapping attitude, confidence, and skills towards the use of a computer, as students use an electronic learning environment, which could be a disadvantage when being not very 'computer-adjusted'.

Limitations

There are some limitations to this study. First, we exclusively used questionnaires to measure the biological and psychological factors. It is preferred to use a combination of subjective and objective measures to ensure reliability and validity of the measured variables, especially for the biological variables like physical activity (although research shows questionnaire data to be more reliable in adults compared with adolescents [Slootmaker, Schuit, Chinapaw, Seidell, & Van Mechelen, 2009]). Within this population (i.e., students who study from their own home and live across the country), it is a logistical challenge to use objective measurements. Besides this, the ALOUD study is an exploratory research. Therefore, we chose to perform this research using an online questionnaire.

Second, because of the broad time frame of participation, there could be unintended differences between participants. At time of participation, some students had not even started their course yet, while others were already at the end of the course.

Furthermore, it took students approximately 60 minutes to participate. To heighten the response rate, participants were given the opportunity to pause and return to the questionnaire at another chosen time. Because of this opportunity, there might be a separation between participants who filled out the questionnaire at once and those who divided the questionnaire into more parts spread out over several weeks. In future research, it is preferred to standardize the way of filling out the questionnaire.

Finally, we looked at learning performance after 14 months (i.e., duration of one course). It would be valuable to extend this time frame and to follow students throughout their study career at the OUNL.

Acknowledgements

We are grateful to Nick Daems and Jaap Murre of UvA NeuroTest BV for developing the digital cognitive tests, and Bogdan Boermans for his assistance with LimeSurvey. We would also like to thank Charlotte Wolff and Ine Verstappen for their contribution in the translation of the questionnaires, and Astrid Kokkelkorn for her assistance in generating the data from the exam registration database.

Ethical considerations

The ethical review committee of the OUNL approved the study. At the start of the online questionnaire, participants had to actively tick a box in order to agree to an informed consent form. With this, they declared that they were aware of personal data being gathered, gave permission to data being gathered and analyzed, and were aware that participation was fully voluntary and that they could with draw at any time without explanation. Without ticking this box, participation was not possible.

CHAPTER 3

Characteristics of successful, non-successful and non-starting students in adult distance education

Research investigating the characteristics of students who are successful, non-successful or non-starters in their study is scarce when it comes to adult open distance higher education. Of the available research, most involves small samples of students and uses persistence and dropout as measures, which are often inconsistently defined. Therefore, an investigation reporting on the characteristics of students within clearly defined groups using a large sample is desirable. The current observational longitudinal study investigated many possible characteristics of the three above mentioned groups of students, derived from a fairly large dataset (N=1991). The characteristics, ordered according to Rovai's model of persistence, involve measures related to demographics, health, life satisfaction, lifestyle, cognitive performance, study intention, living situation, computer abilities, work, learning restrictions (i.e., learning or psychological disorder), and medicine use. Descriptives are given for each characteristic and differences between the three groups were analyzed. The analyses revealed many differences in the characteristics between successful, non-successful and non-starting students. Most of the differences found were between the non-starters and the other two student groups. Regarding differences between successful and non-successful students, students which were healthy and satisfied with life, were more likely to be successful, as also reflected by a lower body mass index. All differences are extensively discussed and provide new and relevant input for distance education institutions and researchers investigating success, persistence and/or dropout in distance education.

This chapter was based on: Gijselaers, H. J. M., Neroni, J., Kirschner, P. A., & De Groot, R. H. M. (under revision). Characteristics of successful, non-successful and non-starting students in adult distance education. *The International Review of Research in Open and Distributed Learning.*

Introduction

Distance education (DE) is gaining increasing interest in adult students due to the increasing need to improve professional knowledge and experience with regard to job demands (Eurydice, 2011). Furthermore, due to increased life expectancy and better health care (The Netherlands: Centraal Bureau voor de Statistiek, 2014; Worldwide: United Nations, 2012) people are living longer and also working longer as retirement ages increase. To maintain and continue developing professional knowledge and skills far into adulthood (Eurydice, 2011), people increasingly choose for formal continuing education. This adult population generally has to combine family and work responsibilities with study, which could be why they choose DE. And this DE is increasingly making use of Information and Communication Technologies allowing them to study when and where they choose, often at a self-determined pace.

Success, persistence and dropout is a subject of interest in DE as attrition rates there are higher than in conventional education (40- 60%; Berge & Huang, 2004; Yukselturk, Ozekes, & Türel, 2014). Many studies have investigated the characteristics of successful/persistent students and/or dropouts in adult DE (e.g., Kemp, 2002; Willging & Johnson, 2009), but definitions for success/persistence and dropout are far from uniform across studies (Grau-Valldosera & Minguillón, 2014; Lee & Choi, 2011). In the study reported here, along with successful students, a discrimination was made between non-successful and non-starting students. The current study investigated the characteristics of these three types of students and their relationship with success/ persistence.

Definitions

In order to carry out this study, the following commonly used terms needed to be carefully defined: distance education, persistence, and dropout.

Distance education

This article focuses on formal adult open DE at the higher education level. This type of formal education is usually characterized by terms as: distance learning; online learning; online education; web based learning; asynchronous learning; and e-learning (Schlosser & Simonson, 2009), although they are not always semantically proper for this type of education. In this article, when the term DE is used, we refer to this contemporary adult open DE on a higher education level as made available by certified open universities.

Persistence

The literature on the characteristics of successful students in DE often uses the term persistence. Persistence is "the behavior of continuing action despite the presence of obstacles" (Rovai, 2003, p. 1). This definition, however, is not fully congruent with success. A student can be quite persistent, but formally unsuccessful as (s)he may,

despite persistence, not be able to obtain any course credits. Other researchers claim persistence to be analogous to progress (Kemp, 2002), which seems logical as persistent students - all things being equal - should eventually succeed because of their persistence. A more persistent student will be likely to book more study progress. However, if study progress is studied over a relatively short period of time, a student could unjustly be classified as non-persistent as he or she did not yet accrue any course credits in that time period.

Although persistence and success seem highly similar, they are not equivalent. Success, measured by formally achieving course credits in the subscription period, is a more simple definition, which is clearly defined. By stipulating a definition for success, one can argue that persistence is fairly congruent in most cases. Successful students are, namely, always included in the group of persistent students. Considering this congruency and since a lot of research focuses on persistence, the persistence literature was taken into account.

Dropout

Many empirical studies investigate the characteristics of dropouts in DE. Dropout is important for DE as percentages are high due to the often open character of the educational program (Berge & Huang, 2004). However, the definition of dropout in the literature varies and is often unclear (Lee & Choi, 2011). Although attempts have been made to clearly define the term (e.g., Grau-Valldosera & Minguillón, 2014), there is little uniformity. In the literature, dropout can be defined as non-successful students (e.g., Willging & Johnson, 2009) or non-successful and non-starting students combined (e.g., Kemp, 2002), not defined at all (e.g., Park & Choi, 2009) or it is unclear which students are considered dropouts (e.g., Yukselturk et al., 2014). The distinction between different types of dropouts should be taken into account, as it can provide interesting information upon which DE institutions and researchers can act.

While it is safe to assume that successful students are persistent, non-successful students can be persistent but not (yet) successful. Non-starting students are unlikely to be persistent as they did not start their study. However, they cannot be safely considered 'real' dropouts as they can always resume their study at any given point. Sometimes, these students are referred to as *stopouts*; students that stop, but continue at a later point (Berge & Huang, 2004). Taking these differences into account, it was chosen not to use the term dropout as a classification term in the current study.

Review of the literature

The current state of research on the characteristics of certain groups of students, in terms of success, persistence and dropout was reviewed. A review article reporting on 35 articles related to dropout and persistence in online courses (Lee & Choi, 2011) provides a good backbone. Lee and Choi included publications over a ten year period ending in 2011. The study did not draw conclusions on demographic characteristics as many studies reported incongruent findings. The demographics that were not

reported were sex and gender. Previous research reported in this review (e.g., Willging & Johnson, 2009) states that there are no age differences between dropouts and non-dropouts. Other research shows that dropout is higher in younger students (Pierrakeas, Xenos, Panagiotakopoulos, & Vergidis, 2004). Categorizing participants in age groups (e.g., Park & Choi, 2009), seems fairly logical as the age range of students is large in DE. However, here, no relation between age and dropout has been found. In this study of Park & Choi, age was measured on three levels, which is very crude considering the age range of DE students.

In their review, Lee & Choi (2011) cannot draw a conclusion regarding sex as results are contradictory. A study with a large sample in which dropout was defined congruent to the definition of non-starters in the current study (Tello, 2007), reported no differences in terms of sex. Studies that Lee & Choi reported on that did find sex differences were small and held other definitions of dropout, incongruent to the current study. Therefore, it is concluded that regarding dropout (i.e., defined as not starting), sex most likely does not play a role. The review revealed that students' previous academic performance was negatively correlated with dropout. Other conclusions in their review (Lee & Choi, 2011) relevant to the current study was that higher work commitments (i.e., fulltime work and/or a greater number of work hours) increased the chance of dropout. And last, that support from other people was an important predictor of persistence (Lee & Choi, 2011).

A major drawback of the reviewed studies (Lee & Choi, 2011), which was also noted by the authors, was that the term 'dropout' was often not clearly defined (i.e., 13 studies, 37%) (e.g., Müller, 2008), and where dropout was defined, definitions differed greatly. Some studies saw non-completers as dropouts (e.g., Kemp, 2002). Other studies saw students who chose not to continue their study as dropouts, even if they successfully finished a course (e.g., Frydenberg, 2007). And even other studies did the same, but only if students officially withdrew as indicated by not re enrolling for future courses (e.g., Pierrakeas, Xenos, Panagiotakopoulos, & Vergidis, 2004). This makes the comparison difficult and practically impossible to explain incongruent findings. Furthermore, many studies used small samples (e.g., Packham et al., 2004; Park & Choi, 2009; Willging & Johnson, 2009) and thus have little power and few possibilities to generalize to a broader scale. In addition, some studies used crude measures for characteristics that can be measured more specifically such as age and educational level (e.g., Park & Choi, 2009). Using more specific measures makes it possible to find potential differences or be more certain in concluding there are none.

As can be seen by this review of literature, there is little congruency in the literature making it difficult to draw conclusions regarding the characteristics of successful, non-successful and non-starting students or dropout and persistence.

Model of persistence

Rovai (2003) proposed a model to explain persistence in DE. He classified four categories of variables that could influence persistence in DE, namely (1) student

characteristics, (2) student skills (factors affecting students prior to admission), (3) external factors and (4) internal factors (factors affecting students after admission). The *student characteristics* focus on variables such as age, gender, ethnicity and level of education. The *student skills* are skills related to the academic knowledge domain such as reading and writing skills, but also academic management skills such as planning. The *external factors* relate to factors such as financial and mental support, work hours, and family responsibilities. The *internal factors* focus on variables such as self-esteem, social integration, and support services. This model was not used when this study was designed. As a result, variables were measured only within three categories of Rovai's model. Still, the model provides a good framework for reporting the results. Most variables were measured in the category *student characteristics*. The variables measured in the current study are be discussed in the light of this model.

Aim of the present study

The aim of the present study is to explore if and how differences in the characteristics of DE students play a role in their success, non-success and non-starting in/of their studies. It reports on variables belonging to three of the four categories from Rovai's model (2003), namely student characteristics prior to admission, student skills prior to admission, and external factors affecting students after admission. The variables within the category *characteristics of students prior to admission* focus on measures related to demographics; health, life satisfaction and lifestyle; cognitive performance; study intention; and living situation. With respect to *skills of students prior to admission* only computer abilities were included. Finally, with respect to *external factors affecting students after admission*, work related measures, learning restrictions (i.e., learning or psychological disorder) and medicine use were used. Descriptives for every group were given and differences were tested.

Methods

Design

The current study had an observational design. Data come from the Adult Learning Open University Determinants (ALOUD) study. The ALOUD study is an investigation of different psychological and biological factors possibly affecting cognition and/or study progress in students participating in DE (Neroni, Gijselaers, Kirschner, & de Groot, 2015). Collected measures in the ALOUD study but not included in this article were biological lifestyle factors and psychological factors. All variables were reported via an online digital survey, which was conducted after registration at the university. After 14 months, which is the standard subscription period, data from the exam registration office provided information on the student groups.

Participants

During 1 year (Sept. 2012 – Aug. 2013), all new students of the Open University of the Netherlands who signed up for one or more regular bachelor or master course(s) were invited to participate. Students can register and start throughout the year as the educational system is modular and the curriculum is not fixed. In addition, the education is self-paced. The university is open to everyone, with the only restrictions that an age of at least 18 years old is obligatory and for entrance at the master level a bachelor diploma is necessary (and possible other requirements based upon the specific prerequisites per master). The approached population size was 4945, 57.5% of those approached responded (N=2842) and 41.3% of those approached (N=2040) fully participated.

Procedures

Participants were invited automatically via the e-mail system of the university 14-21 days after successful registration. The seven days range is because a bulk mailing was sent weekly. Students received a reminder two weeks after the initial invitation and one week later a last reminder by e-mail. Four weeks after the initial invitation, a phone call was made (it was tried to reach participants in the three subsequent weeks) in which potential participants were asked whether they were still interested in participating. If so, they received the original invitation once more when needed and a reminder 6.5 weeks after the initial invitation, which was around 1.5 weeks after the phone call. In case the phone call was made in week 6, the reminder was sent one week later. Participants only received reminders or a telephone call if no full response was recorded.

The survey was administered online using LimeSurvey®, version 1.92+ (LimeSurvey Project Team / Carsten Schmitz, 2012). Full participation cost the participants 45 to 60 minutes on average and it was possible to stop and continue later, allowing participants more freedom in their participation by spreading the time burden. Participants who fully participated could win (5% chance) a gift voucher of €20. The ALOUD study was ethically approved by the local ethical committee of the Open University of the Netherlands. Each participant signed a digital informed consent form, explicating the use of the personal data gathered, voluntary participation, possibility to withdraw at any time, and finally giving their permission to use the data for the described goals. Participants had to click a check-box to agree with the terms mentioned; a mandatory action to start the survey.

Materials

Groups

For the analyses three groups were formed: successful, non-successful and non-starting students. Successful students were students who successfully completed a course within the subscription period. Non-successful students were students who did not successfully finish a course within the subscription period, but did attempt an

official examination. The other group – called non-starting students – did not attempt an official examination.

Characteristics

Table 1 below indicates the four categories of Rovai's model (2003) as discussed in the introduction. Per category is indicated which types of variables were investigated. As explained, Rovai's model was not used when this study was designed. As a result, the fourth category *internal factors affecting students after admission* does not contain any variables. Moreover, most of the variables fall within the first category. As the total number of variables investigated is large (i.e., 35 separate variables), these are specifically explicated in the appendix 1.

TABLE 1. Information on the measured characteristics

Rovai's category	Type of variables
Characteristics of students prior to admission	Demographics Health, life satisfaction and lifestyle Cognitive performance Study intention Living situation
Skills of students prior to admission	Computer abilities
External factors affecting students after admission	Work related measures Learning restrictions (learning or psychological disorder) Medicine use
Internal factors affecting students after admission	No variables in this category

Analyses

Descriptives and contingency tables were requested for interval and categorical variables, respectively. Subsequently, the differences were statistically analyzed with an ANOVA for the interval measures. Correlations were requested for the relation between the categorical variables, using Cramer's V. Cramer's V is a robust non-parametric test that is suitable for indicating correlations between nominal variables, especially if tables exceed a 2 x 2 design (Field, 2009). A *P*-value below .05 was considered to be significant. All analyses were performed with SPSS (version 20; SPSS Inc., Chicago, IL, USA).

Results

Dataset compilation

The original dataset contained 2842 cases. Participants were excluded if they did not: (1) complete the survey (802 cases) and (2) participate within 9 weeks (49 cases). These exclusions led to a total of 1991 cases in the analyses.

A number of variables did not contain all 1991 cases. In most cases, this resulted directly from the tailored questionnaire. Tailoring made sure participants only needed to answer questions relevant to their situation. For example, if someone stated not to have a job, (s)he did not need to enter the number working hours. Concerning the three cognitive performance variables, a number of people was recoded as missing value because they: (1) made a remark at the end of the survey that something went wrong during the test (73 cases); (2) had a negative result on the Trail Making Test, due to reported problems with the A part (32 cases); or (3) performed below chance level on the N back task (40 cases).

Descriptives

The descriptives of all interval variables can be found in Appendix 2. Tables 2 through 12 display the results organized according to the description mentioned in the section *Characteristics* in the *Methods*.

Analyses

In the same tables where the descriptives are reported, the results of the analyses are reported. The tables representing interval variables (Tables A through B) depict the results of the ANOVA conducted, with the significance of the F statistic and the post hoc comparisons with Bonferroni correction. The tables representing categorical variables (Tables C through D) show the correlation Cramer's V, but only if the reported *P*-value belonging to that statistic is significant, which is also displayed in the respective tables. Following Rovai's model (2003), the results found are reported in text below.

Characteristics of students prior to admission

First, the characteristics of students prior to admission are considered, which are: demographics; health, life satisfaction and lifestyle measures; cognitive performance; study intention; and living situation.

Demographic characteristics

Starting students are generally younger than non-starting students (Table 2). In Table 3, the other results of this section can be found. Categorizing participants in age groups shows that especially young adults (i.e., 18-24 years old) are more likely to start their study when they register and that people between 40 and 49 years old are more likely to belong to the non-starting group of students. No differences were found for sex, meaning that both men and women are equally successful in their studies. Regarding nationality and native language it was found that both variables are predictive for the group students fall into. For nationality, the non-starting group contains more non-Dutch students. Native language was even more significant and had a larger effect size. Here, especially non-Dutch native-language students were not

successful. Students with a higher educational level were more likely to be successful. The educational level of a possible partner was not associated with student group.

Health, life satisfaction and lifestyle measures

All results of this section can be found in Table 4, except for those regarding smoking (Table 5). It was found that successful students have a lower body mass index. Alcohol consumption did not reach significance, indicating that it is not an indicator for the student group. Further, non-smokers were more likely to be successful. It was also found that successful students had a higher life satisfaction. The RAND 36 measures health-related quality of life and provides 9 variables of which most showed interesting results. The general health change variable (i.e., compared with the previous year) was the only one not reaching significance, which seems logical as this concerns health far before the start of the study. General health perception, vitality, and physical functioning scores showed that successful students perceived themselves as healthier than non-starting students. For mental health, successful students perceived themselves as healthier than non-successful students. For the variables physical and emotional role limit, social functioning and pain, successful students perceived themselves as healthier than both other student groups.

Cognitive performance measures

Table 6 displays the results of this section. Successful students performed better than non-starting students on updating and processing speed. The performance on the cognitive function shifting reached significance in the F statistic of the ANOVA, but did not yield any post hoc differences. This means there is an overall relation on all levels with regard to shifting. However, individual comparison does not result in significant differences. Results are in the direction that students with better performance on the shifting task are more likely to be in the successful group.

Study intention measures

Lower expected number of study hours per week was predictive for non-starting. Interestingly, when students started studying, fewer expected study hours was predictive for more success (Table 7). A lower expected number of modules to be attained was predictive for non-starting (Table 7). Whether someone studied for personal or professional reasons was not predictive for the group (Table 8). The study goal that students had when starting their program was predictive for the group they belonged to (Table 8). Especially students with the intention to attain a bachelor degree were likely not to be successful. People with the intention to attain a master degree or a premaster program were on the other hand more likely to be successful.

Living related measures

Results for this section can be found in Table 9. Students living with their (grand) parents or living alone were more likely to be unsuccessful. Students who lived

only with their partner (i.e., without children) were more likely to be successful. For students who had children living at home, the number of children was not associated with student group. Students who lived alone with children were more likely to be unsuccessful or non-starting. However, when students had children and a partner, no major differences were observed.

Skills of students prior to admission

There was one skill measured which was computer abilities for which the results can be found in Table 10. This skill did not prove to be associated with student group.

External factors affecting students after admission

The external factors affecting students after admission that were considered are: work related measures and learning restrictions (i.e., learning or psychological disorder).

Work related measures

It was shown that students who work full time were more likely not to start. Students working part time were more likely to be more successful. Students without work were more likely to be non-successful (see Table 12). In accordance with this, students with more weekly work hours were also more likely not starting (Table 11). The regularity of working times for working students was not associated with student group (Table 12).

Learning restriction measures

The results of this section can be found in Table 13. It was found that students with a learning restriction (i.e., learning or psychological disorder) were more likely not starting and even more likely to be unsuccessful.

Medicine use

Students who used medication that had interfering side effects were more likely to be unsuccessful. On the other hand, students who used medication that did not have cognitively or mentally interfering side effects were more likely to be successful.

Discussion

The aim of this article was to report on the characteristics of DE students with respect to possible differences between successful, non-successful and non-starting students. The results show a number of interesting differences, which will be discussed below according to the categories of Rovai's model of persistence (2003).

Characteristics of students prior to admission

Demographic characteristics

In their review, Lee & Choi (2011) report no conclusion regarding age as results are contradictory. Research reported in this review (e.g., Willging & Johnson, 2009) found no age differences between dropouts and non-dropouts. Other research reported that dropout is higher in younger students (Pierrakeas et al., 2004). The results of the current study show exactly the opposite: Starting students are younger than non-starting students. Interestingly, the definition of dropout used by Pierrakeas et al. (2004) is very congruent with our definition of non-starting. This leads us to conclude that results are – as stated by Lee & Choi (2011) – indeed too contradictory to conclude whether age is truly related to starting. Categorizing participants in age groups (e.g., Park & Choi, 2009), shows more specific information about students as the age range is large in DE. This analysis shows that especially young adults (i.e., 18-24 years old) are more likely to start their study and that people between 40 and 49 years are more likely to belong to the non-starting group, which seems close to the finding that older students are more likely to withdraw (Packham et al., 2004). However, the sample in that study was very small and dropout was not defined. The results found in the current study are not in line with Park and Choi (2009). These authors show no relation, which could be due to the low specificity reflected by the number of groups (i.e., 3) used. For the population investigated in the current study, it is likely that younger students have more time to study than older students, possibly due to having fewer family responsibilities. In addition, financial resources could be an incentive here as well. Young students have relatively less to spend than older students and are therefore likely to consider their choice to register more carefully than older students.

As hypothesized, sex does not play a role as no differences are apparent. Lee & Choi (2011) provide no conclusion on sex differences. Taking a closer look, however, at the investigations which used a definition of dropout that matched the current study (i.e., defined as not starting; Tello, 2007), leads us to conclude that sex does not play a role.

Language and nationality make a difference, which is to be expected as most courses at the Open University of the Netherlands are in Dutch, with non-Dutch students being more likely to be non-starting and non-Dutch speakers being less successful. Students with a higher educational level were more likely to be successful, which is fully in line with previous research, since Lee & Choi (2011) were able to draw solid conclusions concerning this in their review. The educational level of a possible partner was not associated with student group.

Health, life satisfaction and lifestyle characteristics

Taken together, the results on health, life satisfaction and lifestyle characteristics indicate that successful students generally perceive themselves to be healthier. This is the first study in this population showing this relation. It is, however, not unexpected, as healthier (Basch, 2011) and more satisfied people (Schimmack, Diener, & Oishi,

2002) perform better on learning performance measures. In traditional education, a higher body mass index is associated with lower academic performance in children (Taras & Potts-Datema, 2005). In the current study, the same is true for adults participating in distance education. Regarding learning, students with a lower body mass index are more likely to be successful. In children (Gunstad et al., 2008) as well as in adults (i.e., young adults: Fergenbaum et al., 2009; and middle-aged adults: Gunstad, Lhotsky, Wendell, Ferrucci, & Zonderman, 2010), it has been shown that a lower body mass index is associated with lower cognitive performance. Cognitive performance is an important predictor of learning (Diamond, 2013). It seems to be that both cognitive performance and learning performance suffer from a higher body mass index although this cannot be causally concluded as most research in this area is always observational.

Cognitive performance measures

Generally, the results regarding cognitive performance indicate that students with a better performance on executive functions and processing speed are more likely to be successful. This aligns with research in children in traditional education where cognitive performance seems to be an important predictor for learning (Diamond, 2013). However, these results need to be further investigated to draw conclusions with more certainty. A more in depth investigation is being carried out and will be reported on in a separate article.

Study intention measures

The most interesting finding here was that when people started studying, the students with fewer expected study hours per week were more likely to be successful. This is surprising, as common sense would predict people planning/expecting to invest more time to be more successful. Non-starters tend to have fewer expected study hours per week and also a lower expected number of modules to be attained. Whether someone studied for personal or professional reasons was not predictive for student group. The program in which students studied, however, was predictive for student group: Students with the intention to attain a bachelor degree were more likely to be not successful. People with the intention to attain a master degree or a premaster program were on the other hand more likely to be successful.

Living related measures

The living situation predicted whether students are successful. Results are in line with social support theory (Crean, 2004) and the review of Lee & Choi (2011). Students living with a partner were more successful. Living with children seemed to distract from studies, as these students tend to be more unsuccessful. However, there was no difference when a student lived with a partner as well as children.

Skills of students prior to admission

One variable measured skills prior to admission, which was the measure computer abilities. Computer abilities can be important in DE nowadays as electronic learning environments are often used that require a certain ability in working with a computer. However, the measurement of computer abilities did not prove to be associated with student group.

External factors affecting students after admission

Quite a number of studies investigated work related measures. Whether it was type of working contract (i.e., full time, part time or no job) or number of working hours, both showed that more working is associated with dropout. The results in this study indicate the same and are in accordance with the findings collectively reported in Lee & Choi (2011). As we also investigated success, it was shown that part time working students were more likely to be successful and non-working students were more likely to be non-successful. Regularity of working times for working students was not associated with student group. Last, as expected (see appendix 1), learning restrictions (i.e., following a psychological or learning disorder) and medicine use were predictive for the group students belonged to.

Strengths and limitations

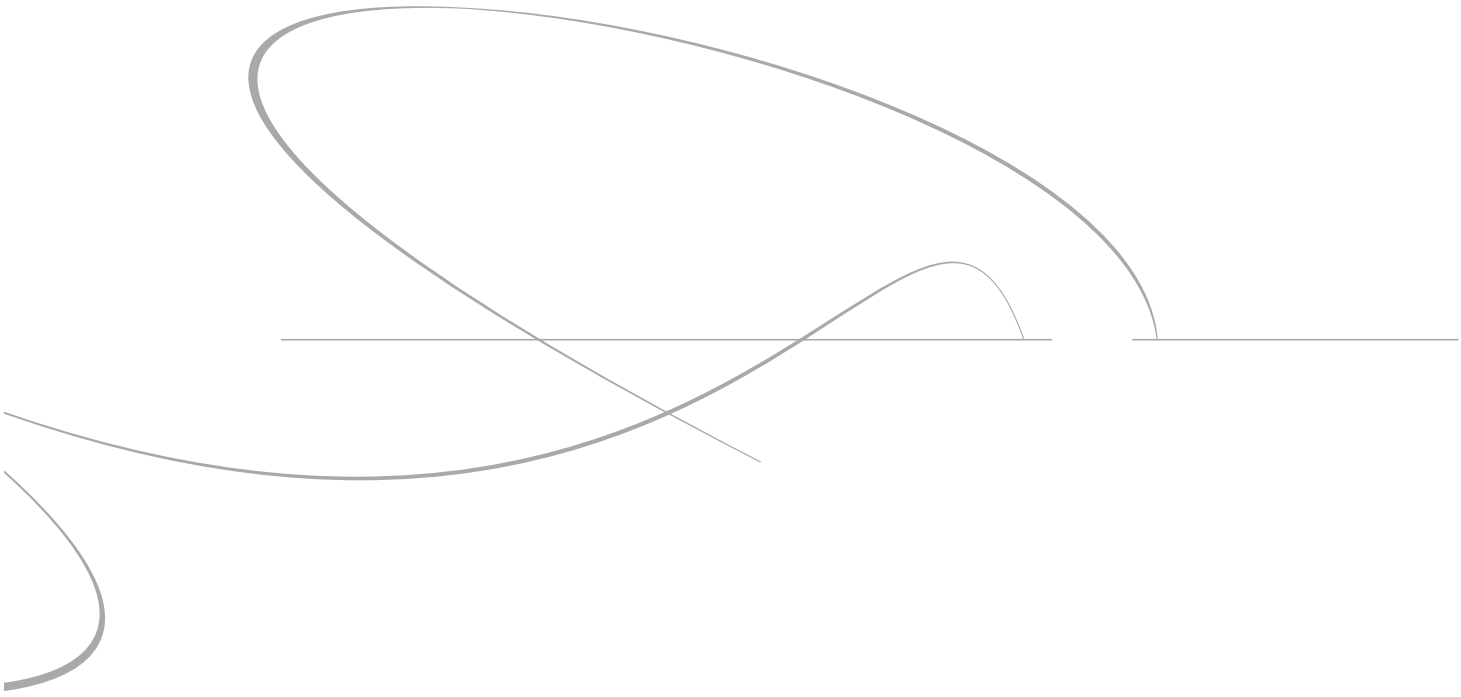
This strengths of this study are multiple. First, it uses a very large sample, especially when compared with existing studies reported on in the literature (e.g., Packham et al., 2004; Park & Choi, 2009; Willging & Johnson, 2009). This makes it possible to generalize the results to a broader group. Second, the study makes a clear distinction between successful, non-successful and non-starting students. Most reported studies are based on persistence and dropout, for which the definitions are often not congruent. Furthermore, because of the use of a non-starting group of students, the dropout students that are unclearly defined in other research (Grau-Valldosera & Minguillón, 2014; Lee & Choi, 2011) are now taken apart into two more clearly defined groups. This makes the current study an important addition to the current knowledge available on the characteristics of DE students.

The study has a few of limitations. Most important is that the ALOUD study is an observational study which does not allow for causal inferences. Also, the data collected for the independent variables are self-report data, which means that for some variables social desirability may play a limiting role. Finally, the cognitive tests were executed right after the questionnaire and carried an instruction asking the participant to execute these tasks in a quiet place without any distraction. Despite this instruction, the environment in which the tests were made were uncontrollable and could therefore possibly have influenced the results.

Conclusions and recommendations

This study shows that specific student groups in DE, classified as successful, non-successful and non-starting students can be distinguished by different characteristics. It also provides valuable information for DE institutions and researchers investigating DE as these results provide a starting point for the development of prediction models and the development of tailored programs. Most of the differences found were between the non-starters and the other two student groups. DE institutions can use these results in determining which students actually start studying and act upon this information by giving personal advice to students. When it comes to differences between successful and non-successful students, clear differences are observed especially in the *health, life satisfaction and lifestyle* section. Students which were healthy and satisfied with life, as also reflected by a lower body mass index, were more likely to be successful.

For DE institutions and researchers investigating DE it is recommended to take the discussed variables into account when predicting success, non-success, non-starting, persistence and/or dropout in DE. For students it is recommended to maintain a stable and healthy constitution to perform more successful in DE.



CHAPTER 4

Physical activity and sedentary behavior do not predict study progress in adult distance education

Previous research has shown that physical activity and sedentary behavior are related to learning performance in traditional education. It is of interest to investigate these relations in distance education as students often have full time schedules and must make choices that traditional students do not. In an observational longitudinal study, physical activity and sedentary behavior of 981 students were analyzed with multiple regression analysis. Analyses showed neither physical activity nor sedentary behavior was related to study progress. Nevertheless, it is recommended that students pay attention to healthy behavior with regard to physical activity and sedentary behavior, as health/cognitive benefits are proven.

This chapter was based on: Gijselaers, H. J. M., Kirschner, P. A., Verboon, P., & De Groot, R. H. M. (submitted). Physical activity and sedentary behavior do not predict study progress in adult distance education. *Learning and Individual Differences*.

Introduction

While physical activity has been shown to have a positive effect on academic achievement in children (Fedewa & Ahn, 2011), sedentary behavior has been shown to have a negative effect (Tremblay et al., 2011). These findings account for children in traditional education (TE). However, to our knowledge, there is no research that deals with the relation between physical activity/sedentary behavior and study progress in adult students participating in distance education (DE).

This population is important as life expectancies keep rising and the fastest growing population group in most countries is that of older adults (The Netherlands: Centraal Bureau voor de Statistiek, 2014; Worldwide: United Nations, 2012). As a result of both changing policies with respect to retirement age and a rapidly changing knowledge-based economy, people also have to work and learn longer. Although certificates and diplomas usually remain valid for the entire duration of a person's life, the knowledge, skills and competencies needed in one's work change. Thus, there is an increasing need for people to develop their professional knowledge and experience far into adult age (Eurydice, 2011), often through participation in continuing formal education. An increasingly preferred form of education (both formal and informal) is DE, which allows for the liberty of studying at one's own pace and schedule. Information and Communication Technology (ICT) and especially the Internet provide useful solutions to reach students that are not able to attend meetings during regular times or are not able to travel for the education they want. DE combines education with ICT and allows students to study at their own pace and schedule.

This study was executed among students of this type of DE, characterized by mainly online learning. The goal of this study was to evaluate whether their physical activity and/or sedentary behavior were related with their study progress.

Mechanisms

Different mechanisms may be responsible for the positive effects of physical activity on learning (for a detailed overview see: Barenberg et al., 2011). Physical activity increases cerebral blood flow, the blood flowing to and through the brain. This, in turn, heightens blood supply, delivering more nutrients (e.g., glucose and oxygen) to the neurons, what may increase their function and as a result possibly enhances learning (Timinkul et al., 2008). The release and production of neurotransmitters and neurotrophins (i.e., proteins that promote development, function and survival of neurons) is also a result of physical activity (Winter et al., 2007). According to Van Praag (2009), this release leads to:

- elevated levels of neurogenesis, the process of neuron creation
- higher synaptic plasticity, the process of strengthening or weakening synaptic bonds
- higher spine density, the increase in the occurrence of possible synaptic locations

- angiogenesis, the process of creating new blood vessels from other vessels
- elevated levels of vascular growth factors, increase in factors that enhance blood vessel growth.

These neurophysiological changes are often caused by epigenetic changes (i.e., changes in the accessibility of the DNA enabling or blocking transcription) following physical activity, which lead to a higher transcription and as a result a higher release of these growth factors, neurotransmitters and neurotropic factors. The ultimate result is an increase in brain plasticity (Kaliman et al., 2011), a benefit for learning.

Distance education versus traditional education

Participants in this study are students of the Open University of the Netherlands (OUNL). The majority of these students is adult, often with an age between 25-45, which is congruent with the typical characteristics of a DE student (Latanich, Nonis, & Hudson, 2001). These students often have a full time employment, a partner and children, which is logical as these characteristics are positively associated with age. This also means that their time to study is limited. This is in sharp contrast with TE, which is characterized by children and young adolescents, without any of these 'adult' responsibilities and constraints. This means that comparing findings on the relation between physical activity and sedentary behavior on the one hand, and achievement, performance and/or progress between traditional and DE on the other is difficult because of differences not only in the educational setting (i.e., face-to-face vs. distance), but also differences in characteristics of the students.

Physical activity

There has been no research carried out dealing with the relation between physical activity and study progress in DE. Therefore, we will shortly review the literature present on this relation in traditional, face-to-face education. Burkhalter and Hillman (2011) state in their review that there is no clear consensus with respect to the relation between physical activity and academic achievement in children noting that the research carried out indicates either a positive relation between physical activity and academic achievement or no relation at all. Despite this, physical activity is still regarded as beneficial since time spent on physical activity does not impair academic achievement (Spitzer & Hollmann, 2013), while it improves health and physical function (Keeley & Fox, 2009). Other research suggests that there are possible benefits of physical activity on academic achievement, but this cannot as of yet be firmly concluded (see: Shephard, 1996; Taras, 2005; Tomporowski, Davis, Miller, & Naglieri, 2008). A more recent, and more comprehensive meta-analysis, executed over 59 studies of which 39 were carried out with an experimental design, revealed a significant and positive effect of physical activity on academic achievement in children, with an effect size of 0.28 (*SE*=.03) which can be considered to be a small to medium effect (Fedewa & Ahn, 2011). In other words, despite a lack of clear consensus it is safe to state that physical activity appears to have a beneficial effect on

academic performance in children (see recent reviews of Hillman et al., 2011; Singh, Uijtdewilligen, Twisk, Van Mechelen, & Chinapaw, 2012).

Sedentary behavior

The flip side of physical activity is sedentary behavior. Sedentary behavior can actually be seen as not being physically active. However, recently it is more and more viewed as an independent construct (Rhodes, Mark, & Temmel, 2012). As was the case earlier, here too we have found no research concerning the relation between sedentary behavior and study progress in DE. Analog to the previous section, we shortly review the available literature on this relation in TE. A large review study found that there is a negative relation present; the more sedentary behavior exhibited by children, the lower their academic achievement (Tremblay et al., 2011). In the narrative review of 35 studies, no effect size was reported and no meta-analysis was performed. The majority (i.e., 75%) of the studies reviewed, report that academic achievement may be hampered by what they call more screen time (i.e., watching television, playing video games, and using the computer for non-academic purposes). In interpreting these results, however, it is important to note that 32 of the 35 studies were cross-sectional in nature and academic achievement was measured in different ways (i.e., IQ, school grades, grade point average, performance on standardized tests, and self-report questionnaires) (Tremblay et al., 2011). The research in this field is in its infancy.

The present study

The present study evaluated the relation between physical activity and sedentary behavior on the one hand, and study progress on the other, in students of the OUNL, offering formal university-level DE. Study at the OUNL is open to anyone over the age of 18. This study is the first in which the relation between physical activity/sedentary behavior and study progress is investigated in DE. Based on the literature, we propose two hypotheses. First, physical activity is positively associated with study progress: more time spent being physically active, or, more intense physical activity leads to better study progress. Second, sedentary behavior is negatively associated with study progress: more time spent not physically active (e.g., sitting) leads to lower study progress.

Methods

Design

The current study had an observational design. Data were retrieved from the Adult Learning Open University Determinants (ALOUD) study. In the ALOUD study, different psychological and biological factors that could affect study progress in students participating in university-level DE were investigated. Other measures collected in the ALOUD study but not included in this article were biological factors (e.g., sleep,

nutrition), cognition and psychological factors (e.g., motivation, affect, social support). An online digital survey was used to allow respondents to report on their physical activity, sedentary behavior and possible covariates (see Materials section). The survey was conducted after registration at the university. After 14 months, study progress was objectively measured using data from the exam registration office. The time period of 14 months is chosen because this is the standard subscription period when registering for a course.

Participants

During 1 year (Sept. 2012 – Aug. 2013), all new students of the OUNL who signed up for one or more regular bachelor or master course(s) were invited to participate in the study. At the OUNL, students can register and start throughout the year as the education system used is modular and self-paced, open to everyone who is 18 years or older, and the curriculum is not fixed. The approached population size was 4945, 57.5% of those approached responded (N=2842) and 41.3% of those approached (N=2040) fully participated.

Attrition rates in this population are high, as more than 50% of the responders in the investigated population did not complete any course after 14 months. Many students simply report not having started studying. As the goal is to predict study progress, including students without any study progress because they did not study could confound possible relations. However, excluding those without progress is not desirable as they may have studied, but without successfully finishing a course. To make a more valid data selection, an official examination attempt was used as a proxy of having studied. This way, the high number of students that had bought a course but never attempted to officially finish it or who did not intend to attain course credits (i.e., buying the course purely out of interest) could be excluded. The information on exam attempts was provided by the exam registration office.

Procedures

Participants were automatically invited to participate via the e-mail system of the university 14-21 days after successful registration. The 7 days range was because a bulk mailing was sent weekly. Students received a reminder two weeks after the initial invitation and one week later a last reminder by e-mail. If after 4 weeks there was no full response recorded, the researchers called the student in which potential participants were asked whether they were still interested in participating (if the student was not reached, the researchers tried again for 3 subsequent weeks). If the response to the phone call was positive, the student received the original invitation again – if needed – and a reminder 6.5 weeks after the initial invitation, which was around 1.5 weeks after the phone call. In case the phone call was made in week 6, the reminder was sent 1 week later. Participants only received reminders or a telephone call if no full response was recorded.

The survey was carried out online in LimeSurvey®, version 1.92+ (LimeSurvey Project Team/Carsten Schmitz, 2012). Full participation cost the participants 45 to 60 minutes on average and it was possible to stop and continue later, allowing participants more room to participate by spreading the time burden. Participants who fully participated could win (5% chance) a gift voucher of €20. The ALOUD study was approved by the ethical review committee of the OUNL. Each participant signed a digital informed consent form, explicating the use of the personal data gathered, voluntary participation, ability to withdraw at any time, and permission to use the data for the described goals. Participants had to click a check-box to agree with the terms mentioned; a mandatory action to start the survey.

Materials

Dependent and independent measures

The dependent measure was the participant's study progress; the number of successfully completed modules (i.e., 4.3 European Credits per module) 14 months after date of registration. The independent measures were extracted from the Short Questionnaire to ASsess Health-enhancing physical activity (SQUASH), which was used to measure physical activity. The SQUASH has a reasonable reliability (r = .58) and validity (r = .45) (Wendel-Vos, Schuit, Saris, & Kromhout, 2003). Sedentary behavior was measured using a self-developed questionnaire based on the principle of the SQUASH. Questions on sedentary behavior regarded sedentary behavior during work, transportation, leisure time (i.e., on work and free days), resting, and sleeping. Physical activity was calculated as a weekly activity score; an accumulated product score of intensity of the activity multiplied by the minutes spent on the activity. This way, the end variable corrected directly for intensity. Sedentary behavior was calculated as a total score of minutes of sitting, lying, and sleeping per week.

Covariates

The covariates included in this study were:

- age, as memory performance declines with increasing age (Grady & Craik, 2000), possibly hampering learning efficiency;
- sex, as there are profound sex differences in intelligence (e.g., on the domains of memory, reasoning and science) which could influence study progress. There are intellectual domains where males excel females (e.g., spatial reasoning) and vice versa (e.g., verbal fluency) (Halpern, 1997);
- number of working hours per week, as common sense and literature (Eppler & Harju, 1997) suggests that more working hours lead to less study progress, as less study time is remaining. However, it has been found that workers with less than 20 work hours per week perform worse than their counterparts working more (Taplin & Jegede, 2001), making it important to correct for working hours separately;
- expected average number of study hours per week to be invested (as reported by the students), as more time invested is likely to lead to better results (Bernt & Bugbee, 1993);

- nationality, as non-Dutch nationals could experience difficulties since most courses are in the Dutch language;
- native language, as non-Dutch speakers could have more difficulties with the language;
- body mass index (computed from weight and height), as physical activity and sedentary behavior are associated with body mass index (for physical activity, see: Church et al., 2011; for sedentary behavior, see: Sugiyama, Healy, Dunstan, Salmon, & Owen, 2008), and body mass index is negatively associated with learning performance (Crosnoe & Muller, 2004);
- level of education (ordinal variable with eight levels), as previous level of education has been found to be a significant predictor of academic success for DE students (Bernt & Bugbee, 1993);
- computer abilities (measured via a self-developed questionnaire mapping attitude, confidence, and skills towards the use of a computer), as students use an electronic learning environment, which could be a disadvantage when being not very 'computer-adjusted';
- study motive (personal or professional), as intrinsic motivation is a better motivator for learning than external triggers (Ryan & Deci, 2000);
- study goal (expected number of completed modules after 6 months), provides a clear estimation of the expectation and hence the intention of the study progress to be made;
- alcohol consumption, as it has been found to influence study progress (Singleton & Wolfson, 2009);
- life satisfaction (Diener, Emmons, Larsen, & Griffin, 1985), as more satisfaction is synergistic with better learning (Seligman, Ernst, Gillham, Reivich, & Linkins, 2009).

Analyses

As expected, the data on the dependent measure (i.e., study progress) revealed a negative binomial distribution. Because the current study concerns part-time DE, it was expected that most students will attain an average of 2 to 3 modules per year (i.e., based on data from internal year reports). Students either completed no course at all, or, had completed one, two, three or four courses. A small proportion of the sample had attained more courses, up to 20. Thus, the distribution of the dependent variable was highly skewed and resembled a negative binomial distribution. Therefore, a negative binomial generalized linear regression was conducted. A *P*-value below .05 was considered to be significant. Univariate outliers on the variables of interest (i.e., independent variables) were excluded before analyses (i.e., a standardized *Z*-value higher than the absolute value of 3.29). A covariate model was built including all covariates, after which non-significant predictors were excluded, yielding model A.

Then, model B was tested by adding the physical activity and sedentary behavior measures to model A. All analyses were performed with SPSS (version 20; SPSS Inc., Chicago, IL, USA).

Results

Dataset compilation

The original dataset contained 2842 cases. Participants were excluded if they: (1) did not attempt an exam (1238 cases); (2) did not complete the survey (414 cases); (3) did not participate within 9 weeks (32 cases); (4) made a remark at the end of the survey that led to exclusion (1 case); (5) had missing values in the physical activity and sedentary behavior variables (164 cases); and (6) univariate outliers were excluded as mentioned (12 cases). All exclusions mentioned led to a total of 981 people included in the analyses.

Descriptives

Table 1 provides an overview of the descriptives of all the variables, measured at the interval level. Table 2 provides an overview of the dichotomous variables. The assumption of no multicollinearity was met as the correlations between all predictors were low (i.e., below .4). This was also indicated by high tolerances (i.e., above .7; Field, 2009). All predictors (i.e., covariates and independent variables) were included in the evaluation of this assumption.

As can be seen in Table 1, the standard deviation differs among the variables, imposing a threat to the reliability of the results as homoscedasticity is an important assumption in linear models. Large differences in variances can distort the estimation of the model fit and parameters. Therefore, the variables were transformed to align the variances prior to the analyses.

TABLE 1. Descriptives of all included variables measured at interval level

Variable	Mean	SD
Study progress (successfully completed modules in 14 months)	2.61	2.65
Total work hours per week	26.58	15.57
Expected study hours per week	13.27	7.33
Age (years)	35.63	10.82
Educational level	5.93	1.36
Body mass index (kg/m^2)	23.89	4.09
Computer abilities (scale score)	43.06	5.64
Expected number of attained modules	2.25	2.35
Total weekly alcohol consumption (standard glasses)	3.48	5.15
Life satisfaction (scale score)	25.33	5.46
Physical activity (min/week corrected for intensity)	7134.57	3563.74
Sedentary behavior (min/week)	6245.25	1411.92

TABLE 2. Descriptives of all included variables measured at nominal or ordinal level

Variable	Number	Percentage
Sex		
Male	360	36.7
Female	621	63.3
Nationality		
Dutch	889	90.6
Non-Dutch	92	9.4
Native language		
Dutch	932	95.0
Non-Dutch	49	5.0
Study motive		
Personal	559	57.0
Professional	422	43.0

Results of the analyses

Chi square comparisons revealed that model A was better than the null model (i.e., an intercept only model); χ^2 (5, N = 981) = 81.85, $p < .001$, indicating that model A fits the data significantly better than the null model. Comparison of model B with model A revealed that model B did not fit the data better, χ^2 (2, N = 981) = 3.95, $p = .14$. This means that adding physical activity and sedentary behavior to model A did not explain study progress better. The regression results for models A and B can be found in Table 3. Physical activity and sedentary behavior are not associated with study progress. This means that the amount/intensity of physical activity and/or sedentary behavior are not predictive for study progress after 14 months.

TABLE 3. Descriptives of all included variables measured at nominal or ordinal level

Predictor variable	β (standardized)	Significance (p-value)
Model A (χ^2=81.846, df=5, p<0.001)		
Expected study hours	.125	<.001
Expected number of completed modules after 6 months	.150	<.001
Alcohol consumption per week	.057	.042
Life satisfaction	.093	.002
Native language[1]	.548	<.001
Model B (χ^2=85.799, df=7, p<0.001)		
Expected study hours	.125	<.001
Expected number of completed modules after 6 months	.147	<.001
Alcohol consumption per week	.055	.052
Life satisfaction	.099	.001
Native language[1]	.546	<.001
Physical activity intensity score	-.038	.198
Sedentary behavior in minutes per week	.041	.164

[1] *This dichotomous variable is not standardized*

Discussion

The aim of the present study was to examine whether physical activity and sedentary behavior were associated with study progress in DE. Neither physical activity nor sedentary behavior was associated with study progress. These results indicate that physical activity, as well as sedentary behavior, appear to have no relation with study progress in DE, in contrast with the results obtained in TE. Important to note is that the results obtained here are applicable to adults. These results are highly important as there has been no research focusing on this relation in DE. The adult students served by this educational type are an increasingly important group due to their increased preference for this type of education because of the flexibility and the need for knowledge development in society and lengthening of employment age, demanding lifelong learning.

Because of theoretical underpinned mechanisms (Barenberg et al., 2011) and findings in TE (i.e., see reviews of Burkhalter & Hillman, 2011 or Singh et al., 2012) positive associations between physical activity and learning were expected in the current study. However, results indicate no relation whatsoever. First of all, it could be possible that physical activity is simply not related to study progress in DE. However, this seems unlikely, considering the physiological processes that occur following physical activity. Therefore, we compare our population with students participating in tradition education and try to provide possible explanations. The characteristics of the DE students are that they are adult, mainly with an age between 25-45, which is in accordance with previous research describing typical distance students (Latanich et al., 2001). In sharp contrast with TE, DE students often have a full-time employment, a partner and children, which means their study time is limited. Because of these time restraints it could be likely that students being more physically active spend less time studying. This could confound positive effects of physical activity as not enough is learned in the first place, meaning the physiological mechanisms cannot amplify learning as too little is learned in the first place. Furthermore, next to the differences in populations between traditional and DE, there are also differences in educational setting. Most research with children focuses on academic achievement (e.g., grades in a course, standardized test scores, etcetera). However, in the current study, study progress was evaluated (i.e., course completion). This could lead to different results as both measures are not only different in terms of outcome, also their generation is highly different. In TE, students have fixed educational curricula which is in contrast with the DE investigated here as the curriculum is not fixed and students can choose any study path they prefer. Still, if both outcome measures in traditional and DE represent learning performance, more physical activity should be related to better performance in both populations. That this cannot be concluded, might then be attributable to the totally different characteristics of the two populations.

Sedentary behavior was shown to be unrelated to study progress in the current study, despite the hypothesized negative relation. It could be possible that sedentary

behavior is simply not related to study progress in DE. However, recent research recommends the measurement of specific types of sedentary behavior (Rhodes et al., 2012). It was shown that different types of sedentary behavior (e.g., working on the computer vs. watching TV) are differentially associated with cognition (Kesse-Guyot et al., 2012), which is an important predictor of learning (Diamond, 2013). In addition, in TE specific sedentary behaviors seem to be detrimental for learning as well, as indicated that sedentary behavior was mostly measures as TV viewing (Tremblay et al., 2011). However, research in this area is in its infancy and more research is needed to clarify possible effects or relations of sedentary behavior on or with learning. It seems to be that cognitively active sedentary behaviors such as computer use for learning have a positive influence, while other – more cognitively passive – sedentary behaviors such as TV viewing are detrimental (Rhodes et al., 2012). Unfortunately, data in the current study did not provide information on these specific types of sedentary behavior. Here, it was measured as a general total measure for sedentary behavior. This could mean that if specific types of sedentary behaviors are differentially related to study progress in the current study they could counteract each other yielding no relation in the end. This finding asks for further research in which different sedentary behaviors are taken into account.

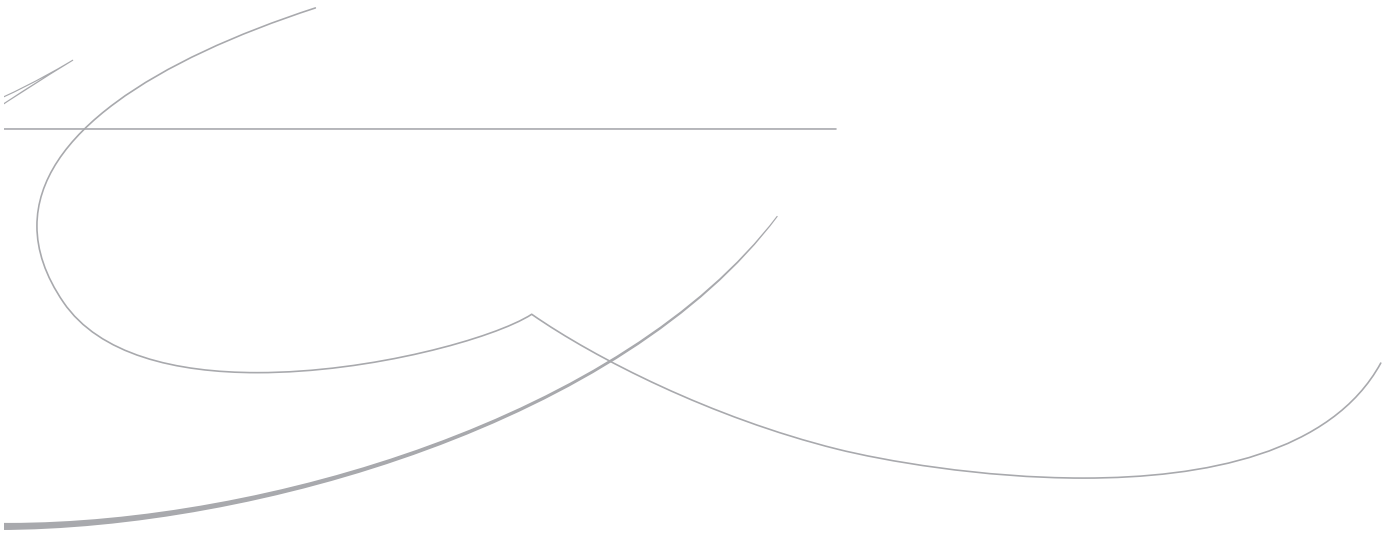
The strengths of the current study are: it is the first of its kind evaluating the relation between physical activity/sedentary behavior and study progress in adults participating in DE. A second aspect is that this study used a large sample providing a high power and decreasing the risk of contracting a type-1 error. Last, multiple possible confounders were controlled for, ruling out possible spurious relations.

There are limitations to the current study. First of all, these results must be interpreted with caution as its observational design does not allow for causal inferences. Second, correctly measuring physical activity via self-administered questionnaires is an often debated topic in terms of reliability and validity (e.g., Helmerhorst, Brage, Warren, Besson, & Ekelund, 2012). Research often shows a discrepancy between objectively and subjectively measured physical activity and/or sedentary behavior, especially in adolescents. However, in adults, a study by Slootmaker, Schuit, Chinapaw, Seidell, & Van Mechelen (2009) using the SQUASH found reasonably good agreement. The questionnaire used in the current study highly resembles the one used by Slootmaker and colleagues (2009) as it is a modified version of the SQUASH (Wendel-Vos et al., 2003), including sedentary questions based on the principle of the SQUASH questions.

We recommend future studies to replicate these findings. Concerning physical activity, we recommend future studies to control for actual study time to investigate the alternative explanation given here that physiological benefits of more physical activity are counteracted by spending less time studying. Last, concerning sedentary behavior, we recommend future studies to focus on specific sedentary behaviors to evaluate whether those are differentially related to learning.

To summarize, the current study shows that physical activity and sedentary

behavior are not related to study progress in adults participating in DE. This is the first orienting study into the relation between physical activity and sedentary behavior with study progress in DE. Research in general shows health and cognitive benefits for physical activity (Hillman, Erickson, & Kramer, 2008) and detriments for sedentary behavior (Rhodes et al., 2012). Taking these considerations into account, we recommend students to pay attention to healthy behavior with regard to physical activity and sedentary behavior.



CHAPTER 5

Chronotype, sleep quality and sleep duration in adult distance education: Not related to study progress

Research in traditional education shows chronotype, sleep duration and sleep quality to be related to learning performance. Research in adult students participating in distance education (DE) is scarce. This study aims to provide knowledge on these relationships in this educational setting. In an observational longitudinal study, chronotype, sleep duration (i.e., for work and free days separately) and sleep quality of 894 students were analyzed in a multiple regression analyses. Students provided information on sleep-related measures and important covariates at the start of their study and study progress was evaluated after 14 months. In line with previous research, chronotype did not predict study progress. These results are in line with previous research that the asynchrony problem is not apparent in DE. Further, sleep duration did not predict study progress, neither as a linear nor as a polynomial term. Third, sleep quality did not predict study progress. Concluding, these results are in line with previous research that the asynchrony problem is not apparent in DE. Also, this study showed sleep duration and sleep quality to be unrelated with study progress, an new and unexpected finding asking for attention and further research. Despite the study's observational nature, findings suggest that students participating in DE may benefit from this type of education as the asynchrony problem appears not to apply here, as students can choose their own study schedule.

This chapter was based on: Gijselaers, H. J. M., Kirschner, P. A., & De Groot, R. H. M. (under revision). Chronotype, sleep quality and sleep duration in adult distance education: Not related to study progress. *Learning and Individual Differences*.

Introduction

Sleep is essential for maintaining proper brain functioning (Cirelli & Tononi, 2008). Insufficient sleep duration and/or quality has been shown to impair school performance in children and adolescents participating in traditional education (Carskadon, 1990; Dewald, Meijer, Oort, Kerkhof, & Bögels, 2010). In addition, the idiosyncratic characteristic chronotype – whether you are a morning or an evening person – has been shown to be influencing school performance in adolescents in traditional education (Escribano, Díaz-Morales, Delgado, & Collado, 2012). However, little research deals with the relation between chronotype, sleep duration, sleep quality and study progress in adult distance education (DE) students.

This population is important as life expectancy is increasing and the fastest growing group is that of older adults (The Netherlands: Centraal Bureau voor de Statistiek, 2014; Worldwide: United Nations, 2012). Retirement age policies are being upwardly revised and our knowledge-based economy is developing quickly; as a result people have to work and learn longer. To compensate for the increasing need to continue to develop professional knowledge and experience far into adult age (Eurydice, 2011), people often participate in formal continuing education. This adult population generally has to combine family and work responsibilities with their study, which is why they often choose for DE. DE increasingly uses Information and Communication Technologies allowing these students to study when and where they choose, often at a self-determined pace. This study was executed among students of this type of DE.

Mechanisms

There is no generally accepted scientific explanation of why we sleep (Cirelli & Tononi, 2008). As research regarding learning progresses, processes become apparent that provide possible explanations. Recent scientific research shows that sleep promotes the consolidation of information acquired during the day (e.g., Diekelmann & Born, 2010; Payne et al., 2012). Slow-wave sleep is especially important as this plays a role in the consolidation of hippocampus-dependent declarative memories. During slow-wave sleep these memories are reactivated and redistributed over networks in the neocortex (Born, 2010), which is important for learning (Ribeiro & Stickgold, 2014). Deprivation of sleep leads to the activation of certain genes which indirectly negatively influence health and cognition. Chronic sleep deprivation adds to this and intensifies the negative effects of acute sleep deprivation on cognition (Möller-Levet et al., 2013), an indicator of performance on the complex measure of academic performance (Diamond, 2013; Furnham, Monsen, & Ahmetoglu, 2009). However, research into the biological mechanisms of sleep – especially regarding sleep deprivation – is in the early stages and full understanding of the exact mechanisms is not possible at this point.

Chronotype

Chronotype is the behavioral reflection of one's underlying circadian rhythm, meaning, whether one is more a morning person or an evening person. Not only physiological factors such as hormone secretion and body core temperature fluctuate with chronotype. Chronotype also influences a broad range of cognitive capacities such as attention, executive functioning and memory (Schmidt, Collette, Cajochen, & Peigneux, 2007). As cognitive performance is a reliable predictor for learning (Diamond, 2013) it is important to account for chronotype.

Chronotype can be measured using self-assessment (i.e., subjective) and sleep times (i.e., more objective, but still via reported sleep times). The first is considered a qualitative assessment, the latter a quantitative assessment (Roenneberg, Wirz-Justice, & Merrow, 2003). These authors show that both of these measurements are in accordance with each other. Despite the congruency of these measures, it is important to recognize that these measures are different, despite that they aim to measure the same construct.

Chronotype changes over age. Children typically have a more early chronotype (Randler & Truc, 2014), but in adolescence this shifts towards the evening as a result of reasons among which could be pubertal development (i.e., a delay in the secretion of melatonin in adolescence, Crowley, Acebo, & Carskadon, 2007) and the need for functional autonomy (Díaz-Morales, Escribano, Jankowski, Vollmer, & Randler, 2014). In adulthood, chronotype tends to shift back towards the morning type (Díaz Morales & Sánchez-López, 2004).

In traditional education, chronotype has a profound influence on learning results. Such face-to-face programs start early in the morning giving early chronotypes an advantage. Evening types tend to get less sleep, awake later and skip breakfast compared to morning types. This leads to lower motivation, which affects school performance as an indirect effect (Boschloo et al., 2012). In addition, early chronotypes tend to achieve higher grades than late chronotypes (Randler & Frech, 2009). In DE, however, no relationship between chronotype and performance has been found (Jovanovski & Bassili, 2007). This could be because these students can choose a learning time better fitting their chronotype. A study in which morning and evening classes were implemented evaluated which chronotypes performed better in which class. The researchers found that morning types performed better in morning classes, compared to evening types and evening types better in evening classes, compared to morning types (Önder, Horzum, & Beşoluk, 2011). The fact that no differences are observed between chronotype and performance in DE provides proof that the asynchrony problem that is apparent in traditional education is weaker, or even not relevant in DE (Horzum, Önder, & Beşoluk, 2014).

Lastly, it is important to recognize that chronotype influences sleep duration, depending on one's social clock. Evening types, for example, may get too little sleep on weekdays because their social clock dictates they awaken early, though they go to bed late, because of their evening preference. On the other hand, morning types

may get too little sleep on weekends when their social clock dictates a nice, but late, get-together Friday evening, resulting in less sleep as morning types wake up early, while evening types can easily sleep longer. Thus, chronotype has an impact on sleep duration, making it important to account for.

Sleep duration and sleep quality

The ideal sleep duration for adults is around 7-8 hours per night, with an inverse U-shaped relation between sleep duration and cognitive performance (Ferrie et al., 2011; Sternberg et al., 2013). Still, many adults get too little sleep as their social clock dictates them to get up early due to, for instance, work responsibilities or children; typical characteristics of DE students.

In traditional education, findings from both cross-sectional and experimental studies show that sleep deprivation (i.e., in the form of duration or quality) leads to poorer learning and lower academic performance (Curcio, Ferrara, & De Gennaro, 2006; Gruber et al., 2014; Short, Gradisar, Lack, & Wright, 2013). In DE, no research regarding the relation between sleep duration and learning performance is available. Though chronotype has been shown to influence sleep duration (Traditional education: Escribano et al., 2012; DE: Önder et al., 2011), it is still important to include sleep duration in the analyses, next to chronotype. This is especially true because DE students are not dictated by their social clock for their study; their study is self-regulated. This means that the shared variance of sleep duration and chronotype in relation to learning performance could be less, which makes sleep duration even more important for the analyses.

Sleep deprivation or impaired sleep quality negatively influences cognitive performance on a wide range of functions including executive attention, working memory, and higher order functions (Durmer & Dinges, 2005). In traditional education, negative effects of sleep deprivation or poor sleep quality on learning performance have repeatedly been shown in children and adolescents (cf. review of Dewald et al., 2010). It has been found in 'emerging adults' (i.e., adults between 18-25 years old) that sleep quality is related to academic performance; specifically, lower sleep quality is related to lower academic performance (Radek & Kaprelian, 2013). This is of interest, as the current study also includes these so-called 'emerging adults'. Only one study is available on the relationship between sleep quality and learning performance in adults participating in DE (Miles, 2014). There, a relation between sleep quality and test grade was found; the lower the sleep quality, the lower the test grade. Clarity is lacking in this study, as it appears that students could have been enrolled in different courses, however, this is unclear. If so, measuring learning performance with a grade would not be correct, as courses differ in terms of difficulty and content. These findings therefore ask for clarification and replication. Further, no research is available on the relationship between sleep quality and cognition in adults, to deduce possible hypotheses from. In contrast, much research is available on older adults (i.e., >65 years). However, there is only a small group of students in this age group in the current study. Because of

this void in knowledge, it is highly interesting to investigate the combination of sleep duration and sleep quality in the adults in this study.

The present study

This study was executed among students of the Open University of the Netherlands (OUNL), an institute providing formal university-level DE to adults. The goal is to provide insight in the relation between chronotype, sleep duration and sleep quality on the one hand and study progress on the other, in adults participating in DE. Based on the findings presented above, we expected: (1) chronotype to be unrelated to study progress, as students can choose their own study schedule and are not dictated by a fixed class schedule; (2) sleep duration to show an inverted U-shaped relation with study progress (i.e., students with an optimal sleep duration tend to have a higher study progress); (3) sleep quality to be positively related to study progress (i.e., students with a better sleep quality tend to have a higher study progress).

Methods

Design

Data from this observational study come from the Adult Learning Open University Determinants (ALOUD) study, an investigation of different psychological and biological factors possibly affecting study progress in DE students (Neroni, Gijselaers, Kirschner, & De Groot, 2015). Collected measures in the ALOUD study not included in this article were other biological measures (i.e., physical activity and nutrition), cognition and psychological factors. Chronotype, sleep duration, sleep quality and covariates were reported via an online digital survey conducted after registration at the university. Study progress was measured objectively using data from the exam registration office.

Participants

During one year (Sept. 2012 – Aug. 2013), all new OUNL students who signed up for one or more regular bachelor or master course(s) were invited to participate. At the OUNL, students can register and start throughout the year as the education is modular and self-paced, open to everyone (with an age of at least 18 years old) and the curriculum is not fixed. The OUNL mainly delivers online education. The approached population size was 4945, 57.5% (N=2842) of whom responded and 41.3% (N=2041) of whom fully participated. Included in the analyses were all participants who fully completed the survey, attempted an exam (see below), participated within 9 weeks (see section 2.3), had no missing data and were not an outlier (see section 2.5).

Attrition rates in this population are high, as more than 50% of the responders in the investigated population did not successfully complete any course after one year. As the goal is to predict study progress, including students without any study progress after one year could confound possible relations. However, excluding those without

progress is not desirable as they may have studied, but without successfully finishing a course. To make a more valid data selection, an official examination attempt was used as a proxy of having studied. In this way, the high number of students that had bought a course but never attempted to officially finish it or who did not intend to attain course credits (i.e., buying the course purely out of interest) could be excluded. The information on exam attempts was provided by the exam registration office.

Procedures

Participants were automatically invited to participate via the university e-mail system 14-21 days after successful registration. The 7 day range is because a bulk mailing was sent weekly. Students received an e-mail reminder 2 weeks after the initial invitation and 1 week later a final reminder. Four weeks after the initial invitation, a phone call was made (with attempts in the three subsequent weeks) asking potential participants whether they were interested in participating. If so, they received the original invitation once more when needed and a reminder 6.5 weeks after the initial invitation, which was around 1.5 weeks after the phone call. In case the phone call was made in week 6, the reminder was sent 1 week later. Participants only received reminders or a telephone call if no full response was recorded.

The survey was administered online using LimeSurvey®, version 1.92+ (LimeSurvey Project Team / Carsten Schmitz, 2012). Full participation cost the participants 45 60 minutes on average and it was possible to stop and continue later, allowing them more freedom to participate by spreading the time burden. Participants who fully participated could win (5% chance) a gift voucher of €20. The ALOUD study was approved by the local ethical committee of the OUNL (cETO). Each participant signed a digital informed consent form, explicating the use of the personal data gathered, voluntary participation, withdrawal at any time, and their permission to use the data for the described goals. Participants had to click a check-box to agree with the terms mentioned; a mandatory action to start the survey.

Materials

Dependent and independent measures

The dependent measure was the participants' study progress, operationalized as the number of successfully completed study modules (i.e., 4.3 European Credits per module) 14 months after date of registration at the institute (i.e., the period in which a student is entitled to take an examination). The independent measures were extracted from various questionnaires. *Chronotype* was measured via reported sleep- and wake-times on work and free days using specific questions from the Munich ChronoType Questionnaire (Roenneberg et al., 2003). Midsleep on free days corrected for sleep debt (MSFSC), was used as the measure for chronotype (Roenneberg et al., 2004). *Sleep quality* was measured with the Pittsburg Sleep Quality Index (PSQI), a well-known and well-validated self-report sleep quality measure (Buysse, Reynolds, Monk, Berman, & Kupfer, 1989). The global PSQI score was dichotomized and used as indicator for sleep

problems. A score higher than 5 was indicative of sleep problems (Aloba, Adewuya, Ola, & Mapayi, 2007). *Sleep duration* was derived from the MCTQ (Roenneberg et al., 2003), for work and free days separately. The reported sleep and wake time were used to calculate sleep duration.

Covariates

The covariates included in this study were:

- age, as memory performance declines with increasing age (Grady & Craik, 2000), possibly hampering learning efficiency.
- sex, as sex differences in intelligence (e.g. on the domains of memory, reasoning and science) have been found which could influence study progress. There are intellectual domains where males excel females (e.g., spatial reasoning) and vice versa (e.g., verbal fluency) (Halpern, 1997).
- number of working hours/week, as more working hours could lead to less study-time and consequently less study progress (Eppler & Harju, 1997). However, research has also found that workers with fewer than 20 work hours/week perform more poorly than their counterparts working more (Taplin & Jegede, 2001).
- expected average of number of study hours/week to be invested (as reported by the students), as more time invested is likely to lead to better results (Bernt & Bugbee, 1993).
- nationality, as education is not 'culture free' and as such non-Dutch people could have more difficulties with the more cultural elements in the educational system.
- native language, as non-Dutch speakers could have more difficulties with the language of study.
- body mass index (BMI; computed from self-reported weight and height), as a large meta-analysis shows an increased risk of obesity for short sleepers (Cappuccio et al., 2008), which could lead to a decrease in cognitive performance (Burkhalter & Hillman, 2011)
- level of education (dummy coded into low, high, and university preparatory level, with low as reference category), as previous level of education has been found to be a significant predictor of academic success for adult DE students (Bernt & Bugbee, 1993).
- computer abilities (measured via a self-developed questionnaire mapping attitude, confidence, and skills towards the use of a computer), as students use an electronic learning environment which could be a disadvantage when one is not very computer literate or fluent.
- study motive (personal or professional), as intrinsic motivation has been found to be a better motivator for learning than extrinsic triggers (Ryan & Deci, 2000).

- study goal (i.e., expected number of completed modules after 6 months) which provides a clear estimation of the expectation and hence the intention of the study progress to be made.
- alcohol consumption, as this has been found to influence study progress (Singleton & Wolfson, 2009).
- life satisfaction (Diener, Emmons, Larsen, & Griffin, 1985), as more satisfaction has been found to be synergistic with better learning (Seligman, Ernst, Gillham, Reivich, & Linkins, 2009).

Analyses

Data were analyzed using multiple linear regression. A *P*-value below .05 was considered to be significant. Outliers on the variables of interest (i.e., independent variables) were excluded before analyses (i.e., a standardized *Z*-value higher than the absolute value of 3.29; Field, 2009, p. 26). A covariate model was built including all covariates, after which non-significant predictors were excluded following a backward stepwise method, yielding model A. Model B was tested by adding chronotype, sleep duration (i.e., for work and free days separately) and sleep quality to model A. Model C was tested by adding 2nd degree terms (i.e., polynomial terms) for sleep duration to model B. All analyses were performed with SPSS (version 21; SPSS Inc., Chicago, IL, USA).

Results

Dataset compilation

The original dataset contained 2842 cases. Participants were excluded if they: (1) did not attempt an exam as mentioned in section 2.2 (1236 cases); (2) did not complete the survey (410 cases); (3) did not participate within 9 weeks (32 cases); (4) had missing data in one of the sleep related variables (254 cases); and (5) were classified as outliers as mentioned in section 2.5 (16 cases). All exclusions led to the analyses reported below with 894 respondents.

Descriptives

Close inspection of the distribution of the dependent variable revealed a binomial distribution. The positive skew and the variance-to-mean ratio being higher than 1 (i.e., 2.43) indicated overdispersion. Thus, along with assuming a negative binomial distribution, a parameter had to be estimated in the model to correct for overdispersion. To conclude, a generalized multiple linear regression was conducted to analyze the data, with a negative binomial distribution (i.e., the GENLIN function in SPSS).

The descriptives for interval variables are depicted in Table 1, appendix 3 also includes the range of all variables. The descriptives for dichotomous variables are depicted in Table 2. The assumption of no multicollinearity was met, following

inspection of the correlations (see appendix 3) and the tolerances. A high correlation was present between the two dummy variables for educational level. High correlation was expected here because it concerns dummy variables. However, both the correlation as the tolerance estimates were still within limits (i.e., below .8 and above .4 respectively, according to Field, 2009), thus no multicollinearity was present. All predictors (i.e., covariates and independent variables) were included in the evaluation of this assumption (see appendix 3).

TABLE 1. Descriptives of all included variables measured at interval level

Variable	Mean	SD
Study progress (successfully completed modules in 14 months)	2.49	2.46
Total work hours per week	30.94	12.11
Expected study hours per week	12.30	6.48
Age (years)	36.15	10.45
Body mass index (kg/m^2)	24.03	3.92
Computer abilities (higher is better ability)	42.72	5.81
Expected number of completed modules	2.26	2.29
Total weekly alcohol consumption (standard glasses)	3.11	4.61
Life satisfaction (higher is higher satisfaction)	25.48	5.43
Sleep duration on work days (hours:minutes)	7:56	0:56
Sleep duration on work days (polynomial)	0.88	1.46
Sleep duration on free days (hours:minutes)	8:30	1:07
Sleep duration on free days (polynomial)	1.23	1.89
Chronotype (sleep debt corrected midsleep on free days; hours:minutes)	3:49	0:55

TABLE 2. Descriptives of all included variables measured at nominal or ordinal level

Variable	Number	Percentage
Sex		
Male (0)	328	36.7
Female (1)	566	63.3
Nationality		
Dutch (1)	806	90.2
Non-Dutch (0)	88	9.8
Native language		
Dutch (1)	848	94.9
Non-Dutch (0)	46	5.1
Dummy educational level high		
Educational level is high (1)	434	48.5
Educational level is other (0)	460	51.5
Dummy educational level university		
Educational level is university (1)	321	35.9
Educational level is other (0)	573	64.1
Study motive		
Personal	502	56.2
Professional	392	43.8
Sleep quality		
Normal sleep	426	47.7
Sleep problems	468	52.3

We hypothesized an inverted U-shape for the relation between sleep duration and study progress. To verify this we inspected the scatter plot of this relationship and confirmed our hypothesis. As linear regression assumes a linear relationship, a U-shaped relation needs to be corrected. To ensure the validity of our analyses, we therefore included sleep duration as a polynomial term. Sleep duration was centered and squared and then included in the model to ensure the modeled relation was linear. The formula for this term is $(x-\mu)^2$.

TABLE 3. Results of the multiple linear regression analyses

Predictor variable	β (standardized)	Significance (p-value)
Model A (χ^2=89.515, df=5, p<0.001)		
Expected study hours	.143	<.001
Body mass index	-.108	<.001
Expected number of completed modules after 6 months	.130	<.001
Life satisfaction	.118	<.001
Native language[1]	.461	.003
Model B (χ^2=92.236, df=9, p<0.001)		
Expected study hours	.143	<.001
Body mass index	-.105	<.001
Expected number of completed modules after 6 months	.131	<.001
Life satisfaction	.115	<.001
Native language[1]	.446	.003
Chronotype	-.019	.540
Sleep duration (work days)	.052	.127
Sleep duration (free days)	-.013	.708
Sleep quality[1]	.013	.833
Model C (χ^2=93.142, df=11, p<0.001)		
Expected study hours	.143	<.001
Body mass index	-.108	<.001
Expected number of completed modules after 6 months	.130	<.001
Life satisfaction	.118	<.001
Native language[1]	.461	.003
Chronotype	-.013	.685
Sleep duration (work days)	.052	.124
Sleep duration polynomial (work days)	-.015	.617
Sleep duration (free days)	-.011	.744
Sleep duration polynomial (free days)	-.020	.518
Sleep quality[1]	.012	.847

[1] *These dichotomous variables were not standardized as this does not enhance interpretation*

Results of the analyses

The results for the tested models can be found in Table 3. Every model was significantly better than the null model (i.e., the intercept-only model) as indicated by the chi-square measure reported in the table. Model A contained all significant covariates. Model B revealed that chronotype, sleep duration (i.e., for both work and free days) and sleep quality were not related to study progress. In model C, the polynomial terms for sleep duration were no significant predictor for study progress. This means

that sleep duration is not related to study progress, also not in an inverted U shaped relation.

In addition, the differences in chi square between the model was investigated to evaluate whether model B or C predicted study progress better than model A. Both model B (χ^2 (4, N = 894) = 2.721, p = .60) and model C (χ^2 (6, N = 894) = 3.627, p = .73) were not significantly better than model A. This means that the investigated sleep variables did not add significantly to the prediction of study progress.

Discussion

The purpose of this research was to investigate relations between sleep quality, sleep duration and chronotype on the one hand and study progress on the other in adult DE students. Previous research in this area is scarce and the combination of these three sleep related variables is new. One out of three hypotheses was confirmed in the analysis. First, chronotype was not predictive for study progress, in line with our hypothesis. Second, sleep duration was not predictive for study progress (i.e., neither for work of for free days), which was in opposition to our hypothesis. Third, sleep quality did not predict study progress, also in opposition to our hypothesis. These results will be discussed separately below.

In agreement with hypothesis 1, chronotype was not related with study progress, replicating the few studies which have investigated this in DE (Horzum et al., 2014; Jovanovski & Bassili, 2007; Önder et al., 2011). This finding is important in light of the asynchrony problem found in traditional education with its set time slots. In such learning situations, people with an evening preference suffer from the requirement to attend classes in the morning as their preferred biological time schedule does not align with the time schedule of the institution. This so called asynchrony problem does not seem to play a role in DE. Important to note is that chronotype in this study was measured as a quantitative measure of circadian timing in the form of phase of entrainment. Thus, a more objective measurement of chronotype was used, instead of a fully self reported chronotype.

Opposite to hypothesis 2, sleep duration was not predictive for study progress, neither as a linear term or as a polynomial term. This accounted for sleep duration on work days as well as free days. No research on the prediction of learning performance using sleep duration is available in a DE setting. This makes these findings highly interesting and a starting point for continuing research. When we compare these findings with research executed within a traditional educational setting, the findings of the current study do not align. In traditional education, sleep duration is clearly related to learning performance (e.g., Taylor, Vatthauer, Bramoweth, Ruggero, & Roane, 2013). Especially interesting is that fact that these findings are not in line with research regarding cognitive performance as an outcome measure (Ferrie et al., 2011; Sternberg et al., 2013). Thus, it could well be that cognitive measures are not a strong predictor

for learning performance in DE. This will be investigated in another study, published in the near future, with data from the ALOUD study (Neroni et al., 2015).

Sleep quality was not predictive for study progress, in contrast to hypothesis 3. This finding does not align with the only other study in this population and field (Miles, 2014). In traditional education, in children and adolescents, from whom we extrapolated the hypothesis, poor sleep quality negatively affects learning performance (Dewald et al., 2010). It is known that sleep quality decreases with increasing age, influencing cognition negatively (Nebes, Buysse, Halligan, Houck, & Monk, 2009). However, little is known about the effects of lower sleep quality on cognition in normal, non-disordered young and middle-aged adults. It could be that adults are less affected by sleep quality in comparison with children, adolescents and older adults, considering that our sample consisted of mainly middle-aged adults. The impact of sleep quality on cognition in this age group is not well investigated, making this finding highly interesting and demanding more in-depth investigation, considering the limitations of this study, mentioned below. Also, the measure of learning performance in traditional education is academic achievement, while in this study it was study progress. It could well be that these measures are too different to compare them.

The strengths of this study are multiple. The large data set provides high power related to the findings and decreases the risk of contracting a type-1 error. Next, this type of education and adult population has rarely been investigated, making these findings new and an important starting point for the field of DE. Last, a major strength is that the study controlled for a large number of possible confounders, eliminating possible spurious relationships. Next to strengths, this study also has limitations. First, it is observational and does not allow for causal inferences, although the design is longitudinal and the hypotheses were theory-driven. All independent measures are subjectively reported, imposing limitations on the interpretation. Subjective sleep duration, for example, can deviate from actual sleep duration. Second, participants had a broad time frame (i.e., 9 weeks) to participate, possibly leading to between-subject differences as some students did not yet start studying, while other were already ending their course. Third, participation took approximately 60 minutes and since participants could participate at their own pace (i.e., stop and return later) this could lead to some distortion. However, the last two points were tackled by the large dataset largely eliminating these possibly confounding factors.

Conclusion

This study confirms the findings of a number of previous studies and strengthens our knowledge within the field of DE. First, chronotype did not predict study progress. Second, sleep duration did not predict study progress and third, sleep quality did not predict study progress. Despite the observational nature of this study and the limitations stated, these findings suggest that students participating in DE may benefit from this type of education as opposed to more traditional face-to-face higher education as the asynchrony problem does not seem to apply here since students can choose their own study schedule.

CHAPTER 6

The consumption of fish, caffeine and/or breakfast does not predict study progress in adult distance education

Consumption of caffeine, fish or breakfast are each separately often investigated in relation to learning performance in traditional education. However, in distance education (DE), there has been no research on this relation. DE is becoming increasingly popular among adults. Therefore, the objective of this study was to investigate whether the relation between the consumption of fish, caffeine and/or breakfast on the one hand and learning performance on the other as found in children is also found in DE students. This population is different from traditional students and characterized by a different profile in terms of age, personal and work responsibilities as well as other demographics. In an observational longitudinal study, the consumption of caffeine, fish and breakfast of 1155 DE students (18 to 76 years old) was used to predict study progress using multiple regression analysis. In an online digital survey, students provided information about their consumption of these nutritional measures and on important covariates, at the start of their study. Study progress was evaluated objectively after 14 months via information from the exam registration office. Analyses revealed that neither the consumption of caffeine nor fish nor breakfast was related to study progress. Consumption of caffeine, fish and/or breakfast does not predict study progress in adults participating in DE, in contrast to traditional students. This study is important as it is the first to report on these relations in this specific age group and educational setting.

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Introduction

Recent research on nutrition has shown that what is consumed is related to learning performance in children and adolescents participating in traditional education (Frensham, Bryan, & Parletta, 2012). However, there has been no research dealing with the relation between nutrition and learning performance in distance education (DE), which is primarily followed by adults.

This specific group is important as the population of most countries is aging because of increased life expectancies. Older adults are the largest growing age group in the Netherlands (Centraal Bureau voor de Statistiek, 2014) and worldwide (United Nations, 2012), and retirement age has increased either voluntarily or due to changes in work laws and/or pension laws. As a result, people are working longer. This, combined with the demands of our knowledge-based society to maintain old and acquire new professional knowledge and skills throughout one's career (Eurydice, 2011), has led to increased participation in continuing formal education. As adults often have family and/or work responsibilities depending on their ages and personal situations, the choice for participating in DE is common. This is facilitated by the fact that DE often makes use of Information and Communication Technology (ICT), giving students the liberty to study anytime, anywhere and often at their own self-determined pace.

It is, thus, the question as to whether the effects found in children and adolescents can also be found in adults. It is important to investigate possible nutritional influences on learning performance in a different and increasingly popular educational setting and a different age group than usual research (i.e., research in traditional education). This is because proper nutrition could lead to better brain health and thus to better learning performance. Nutrition is a large field of research. Therefore, the nutritional measures that were recorded in this study were limited to the consumption of caffeine, breakfast and fish, as these measures have also been often investigated in traditional education.

Mechanisms of action regarding learning

Caffeine is the most widely used neurostimulant and prevents binding of the endogenous neurotransmitter adenosine to its receptors by antagonizing them (Nehlig, Daval, & Debry, 1992). Adenosine accumulates in the synapse over continued wakefulness and induces drowsiness, which is prevented by caffeine and thus maintains or restores alertness. Although there are many more mechanisms of action reported for caffeine in the brain, the effects of caffeine on learning are likely to result from the effects of caffeine on alertness and sleep processes. Therefore, the antagonism of adenosine is most likely the mechanism of importance (for other mechanisms, see Nehlig, Daval, & Debry, 1992).

The omega-3 long-chain polyunsaturated fatty acids (n-3 LCPUFAs) – found in fish – are important building blocks for cell membranes, providing the proper permeability

and fluidity, which is important for signal transduction in neurons (Gómez-Pinilla, 2008). In addition, they also directly impact the levels of brain-derived neurotropic factor, a neurotrophin responsible for proliferation, synaptic plasticity, survival and growth of neurons (Van Praag, 2009). These mechanisms of action improve brain plasticity and could influence cognitive and learning processes (Gómez-Pinilla, 2008).

Finally, breakfast consumption is suggested to have direct effects as well as long-term effects. Direct mechanisms of action are increased availability of glucose and other nutrients from which several cognitive and memory processes benefit. Indirectly, regular breakfast consumption could lead to an increased whole-diet adequacy of nutrient intake, which could translate into better cognitive and/or learning performance (Pollitt & Mathews, 1998).

Caffeine consumption

Depending on the way it is used, caffeine can be viewed as a nutrient, a drug or a drug of abuse (Pardo Lozano, Alvarez García, Barral Tafalla, & Farré Albaladejo, 2007). In the current study, caffeine will be regarded a nutrient as habitual caffeine use is investigated in a healthy adult population. Caffeine seems to boost a variety of cognitive functions. Research shows that habitual caffeine intake is related to better long-term memory (Hameleers et al., 2000), alertness (Owen, Parnell, De Bruin, & Rycroft, 2008), reaction time and short term recall (Ruxton, 2008).

However, despite all these cognitive effects and possible resulting effects on measures of learning performance, no persistent effect of caffeine is expected as the effects are purely the result of the reversal of the withdrawal state. The *withdrawal reversal* hypothesis states that caffeine withdrawal (e.g., overnight) leads to lower cognitive performance and alertness and that this is restored by the consumption of caffeine, but that cognitive performance does not exceed 'higher than normal' levels (Rogers, 2007). Much research regarding this hypothesis has been executed and conclusions were mixed, some were in favor (Smit, Cotton, Hughes, & Rogers, 2004) and others against (Smith, Christopher, & Sutherland, 2006). This scientific dispute has been recently reviewed and evidence seems to generally be in favor for the *withdrawal reversal* hypothesis (Rogers, 2014). This would mean that learning processes and the resulting learning performance do not benefit from habitual caffeine use.

Next to direct effects of caffeine on cognitive and memory processes, caffeine also influences sleep processes. People often use caffeine because they think it will enhance their cognitive performance, when they are tired. Despite the fact that research shows caffeine can actually enhance cognitive performance and alertness after sleep deprivation (Magill et al., 2003), research in adolescents shows the use of caffeine later at night could disrupt subsequent sleep processes, which in turn could impair cognitive performance (James, Kristjánsson, & Sigfúsdóttir, 2011). Further research in traditional education shows that learning performance is in fact negatively influenced by caffeine via sleep processes as a possible mediator (Owens, Mindell, & Baylor, 2014). Research regarding executive functions, an important predictor of

learning performance (Diamond, 2013), shows executive functions do not benefit from caffeine consumption in a state of excessive sleepiness resulting from prolonged wakefulness, despite a reduction in sleepiness (Killgore, Grugle, & Balkin, 2012). This means caffeine does not increase higher-order cognitive functions, while exactly these are thought to contribute to learning performance (Diamond, 2013).

Concluding, it is unlikely that the consumption of caffeine will provide benefits to learning performance in healthy adults, considering that there are most likely no consistent long-term benefits of caffeine on cognition following the evidence on the *withdrawal reversal* hypothesis. In addition, higher-order cognitive functions – a prerequisite for learning performance (Diamond, 2013) – do not seem to benefit from caffeine consumption. Furthermore, sleep processes could be impaired following caffeine consumption (Owens, 2014), leading to lower learning performance. However, habitual use in adults is not expected to show a negative relation with learning processes as only a small group will be likely to consume caffeine later at night and hereby disrupting sleep processes and possibly influencing learning performance.

Fish consumption

Although research shows n-3 LCPUFAs – found in fish – are important for normal development, it is disputable whether n-3 LCPUFAs are beneficial for cognition in adults (Stonehouse, 2014). The most important reason for this is that research is limited in young and middle-aged adults. Most research focuses on children, adolescents and older adults (Phillips, Childs, Calder, & Rogers, 2012), often with developmental disorders or cognitive deterioration, respectively (Luchtman & Song, 2013). Research in children, young adults and older adults shows that cognitive processes are enhanced following supplementation of omega-3, a LCPUFA (Frensham et al., 2012; McCann & Ames, 2005; Stonehouse, 2014). However, several strict review studies in children (Tan, Ho, & Teh, 2012) as well as older adults (Sydenham, Dangour, & Lim, 2012) point out that evidence for enhanced cognition, decreased cognitive decline or dementia onset is lacking.

A recent review – summarizing research findings regarding the n-3 LCPUFAs and cognition throughout the lifespan – shows very little research is present regarding young and middle-aged adults. Findings so far are not conclusive and raise the question whether young and middle-aged adults benefit from a diet containing n-3 LCPUFAs (Karr, Alexander, & Winningham, 2011). Only two studies in this age group examined the relation between n-3 LCPUFAs and cognitive performance (Fontani et al., 2005; Kalmijn et al., 2004). Kalmijn et al. (2004) focused on middle-aged adults (45 to 70 years old) and found that n-3 LCPUFAs (i.e., measured from fish consumption using food frequency questionnaires) lowered the likelihood of cognitive impairment. Fontani et al. (2005) focused on young and middle-aged adults (22 to 51 years old) and found that n-3 LCPUFAs supplementation improved attention and reaction time. However, the authors of the review (Karr et al., 2011) report on a methodologically virtually similar study in younger adults (18 to 27 years old) that does not replicate the findings of Fontani et al. (Antypa, Van der Does, Smelt, & Rogers, 2009).

Concluding, evidence for a clear relation between n-3 LCPUFAs intake from fish and learning performance is lacking, as findings in young and middle aged adults are inconclusive. In addition, taking into account the findings in traditional education to derive a hypothesis for adult DE seems incorrect as children and adolescents are still in their development toward adulthood.

Breakfast consumption

A heavily investigated nutritional measure in traditional education is breakfast consumption (Rampersaud, Pereira, Girard, Adams, & Metzl, 2005). Breakfast is an often skipped meal (Mullan & Singh, 2010) and is mostly considered as having direct effects on cognitive performance as it gives the body energy after a night of fasting. In addition to providing direct cognitive benefits after consumption, breakfast can also be viewed as providing long-term benefits as a result of more adequate whole-diet nutrient intake, leading to a better nutritional status (Pollitt & Mathews, 1998), which could translate into better cognitive and/or learning performance.

In traditional education, breakfast consumption is related to academic performance in children and adolescents (Rampersaud et al., 2005). Important to note, is that traditional education is characterized by face-to-face education with fixed schedules. This means that a breakfast directly contributes to the cognitive status in the beginning of the school day. In DE, however, students can determine their own schedule, as they study at their own location of choice and at their own time of choice. Taking into account that most students in DE have work and family (i.e., partner and children) responsibilities, this means that most students often study in the evening, at night or during weekends. The question then arises whether these students will benefit from the direct effects of having breakfast.

Considering the possible long-term benefits of consuming breakfast, as noted earlier, research shows that a more adequate whole-diet nutrient intake is especially important when deficiencies are apparent (Pollitt & Mathews, 1998). However, in the Netherlands – where the current study is executed – and in Europe in general, people are at a low risk for nutrient deficiencies, especially adults (Mensink et al., 2013).

Concluding, it is unlikely to expect direct effects of breakfast consumption on learning performance as students in DE do not tend to study regularly during the morning. In addition, proposed long-term benefits of an adequate whole-diet nutrient intake following breakfast consumption are unlikely as this applies to undernourished people, which are unlikely to be under investigation in the current study. Furthermore, recent research shows that breakfast consumption can be confounded by the last evening meal consumed in the night before (Lamport, Hoyle, Lawton, Mansfield, & Dye, 2011). This is important for the interpretation of a possible relation between breakfast and learning performance.

The present study

This study was executed among students of the Open University of the Netherlands (OUNL), an institute providing formal university-level DE to adults. The goal was to provide insight in the relation between the consumption of caffeine, fish and breakfast on the one hand and study progress on the other, in adults participating in DE. Based on the findings presented above, it was expected that the consumption of: (1) caffeine was unrelated to study progress; (2) fish was unrelated to study progress; and (3) breakfast was unrelated to study progress.

Methods

Design

Data from this observational study originated from the Adult Learning Open University Determinants (ALOUD) study. The ALOUD study is an observational study in which the association between different psychological and biological factors on the one hand and cognition and/or study progress on the other in students participating in DE is investigated. Collected data in the ALOUD study not included in this article were physical activity measures, sleep related measures, psychological measures and cognition. This has been reported in other articles. All data were reported via an online digital survey, which was conducted after registration at the university. After 14 months, study progress was objectively measured using data from the exam registration office. The time period of 14 months was chosen because this is the standard subscription period when registering for a course.

Participants

During 1 year (Sept. 2012 – Aug. 2013), all new students of the OUNL who signed up for one or more regular bachelor or master course(s) were invited to participate. At the OUNL, students can register and start throughout the year as the education is modular and self-paced, open to everyone (with an age of at least 18 years old), and the curriculum is not fixed. The OUNL mainly delivers online education. The approached population size was 4945, 57.5% of those approached responded (N=2842) and 41.3% of those approached (N=2040) fully participated.

Attrition rates in this population are high, as more than 50% of the full responders in the investigated population did not complete any course after 14 months. Many students simply reported not having started studying. As the goal is to predict study progress, including students without any study progress, because they did not study, could confound possible relations. However, excluding those without progress is not desirable as they may have studied, but without successfully finishing a course. To make a more valid data selection, an official examination attempt was used as a proxy of having studied. This way, the high number of students that had bought a course but

never attempted to officially finish it or who did not intend to attain course credits (i.e., buying the course purely out of interest) could be excluded. The information on exam attempts was provided by the exam registration office.

Procedures

Participants were invited automatically via the e-mail system of the university 14-21 days after successful registration. The seven days range is because a bulk mailing was sent weekly. Students received a reminder two weeks after the initial invitation and one week later a last reminder by e-mail. Four weeks after the initial invitation, a phone call was made (it was tried to reach participants in the three subsequent weeks) in which potential participants were asked whether they were still interested in participating. If so, they received the original invitation once more when needed and a reminder 6.5 weeks after the initial invitation, which was around 1.5 weeks after the phone call. In case the phone call was made in week 6, the reminder was sent one week later. Participants only received reminders or a telephone call if no full response was recorded.

The survey was administered online using LimeSurvey®, version 1.92+ (LimeSurvey Project Team/Carsten Schmitz, 2012). Full participation cost the participants 45 to 60 minutes on average and it was possible to stop and continue later, allowing participants more freedom in their participation by spreading the time burden. Participants who fully participated could win (5% chance) a gift voucher of €20. The ALOUD study was ethically approved by the local ethical committee of the OUNL. Each participant signed a digital informed consent form, explicating the use of the personal data gathered, voluntary participation, possibility to withdraw at any time and finally giving their permission to use the data for the described goals. Participants had to click a check-box to agree with the terms mentioned; a mandatory action to start the survey.

Materials

Dependent and independent measures

The dependent measure was the participant's study progress; the number of successfully completed study modules (i.e., 4.3 European Credits per module) 14 months after date of registration (i.e., the period in which a student is entitled to take an examination). The independent measures were extracted from the questions asked in the questionnaire. *Caffeine consumption* was measured as average daily caffeine consumption, in milligram, calculated from reported coffee, tea and energy drink consumption. The frequency of consumption of three types of caffeinated beverages was self-reported. The three types were: coffee, tea (i.e., only caffeinated tea such as black and green tea) and caffeine containing energy drinks. Regarding coffee and tea, a standard cup of 125 ml. was assumed. Regarding energy drinks, a can of 240 ml. was assumed. Participants reported on a 6 point scale on their daily consumption

(less than one, one, two, three, four, five or more). The following scoring was used to calculate the caffeine consumption score: 33, 66, 132, 198, 264, 330 for the coffee type; 16, 33, 66, 99, 132, 165 for the tea type; 38, 77, 154, 231, 308, 385 for the energy drink type. Milligrams of caffeine for each beverage was derived from average beverage caffeine values reported in the literature (Ruxton, 2008). Accumulation of the partial score resulted in the overall score ranging from 0 to 880 mg. of caffeine a day. *Fish consumption* was measured with a questionnaire validated against omega-3 LCPUFAs plasma phospholipid levels (De Groot, Van Boxtel, Schiepers, Hornstra, & Jolles, 2009). The frequency of consumption of three fish types was reported. The fish types were classified according to their DHA content: low (fish fingers, prawns, pickled herring, cod, mussels, plaice, tuna and tilapia); intermediate (trout, raw herring, smoked eel, smoked salmon, canned salmon); high (smoked herring, herring in tomato sauce, mackerel, canned sardines, salmon). Participants reported using a 5-point scale (never, once per month, two to three times per month, once per week, more often than once per week). The following scoring was used to calculate the fish consumption score: 0, 1, 2, 4 and 8 for the 'low' fish type; 0, 2, 4, 8 and 16 for the 'intermediate' fish type; 0, 3, 6, 12 and 24 for the 'high' fish type. The range for the overall score was from 0 to 48, which was validated against EPA and DHA plasma phospholipid concentrations (De Groot et al., 2009). *Breakfast consumption* was measured as a number of days per week that the participants reported to have consumed breakfast. This was a one question item asking "How many days a week do you usually eat breakfast?".

Covariates

The covariates included in this study were:

- age, as memory performance declines with increasing age (Grady & Craik, 2000), possibly hampering learning efficiency;
- sex, as there are profound sex differences in intelligence (e.g., on the domains of memory, reasoning and science) which could influence study progress. There are intellectual domains where males excel females (e.g., spatial reasoning) and vice versa (e.g., verbal fluency; Halpern, 1997);
- number of working hours per week, as common sense and literature (Eppler & Harju, 1997) suggests that more working hours lead to less study progress, as less study time is remaining. However, it has been found that workers with less than 20 work hours per week perform worse than their counterparts working more (Taplin & Jegede, 2001), making it important to correct for working hours separately;
- expected average number of study hours per week to be invested (as reported by the students), as more time invested is likely to lead to better results (Bernt & Bugbee, 1993);
- nationality, as non-Dutch nationals could experience difficulties since most courses are in the Dutch language;

- native language, as non-Dutch speakers could have more difficulties with the language;
- body mass index (computed from weight and height), as it is negatively associated with learning performance (Crosnoe & Muller, 2004);
- level of education (ordinal variable with eight levels), as previous level of education has been found to be a significant predictor of academic success for DE students (Bernt & Bugbee, 1993);
- computer abilities (measured via a self-developed questionnaire mapping attitude, confidence, and skills towards the use of a computer), as students use an electronic learning environment, which could be a disadvantage when being not very 'computer-adjusted';
- study motive (personal or professional), as intrinsic motivation is a better motivator for learning than external triggers (Ryan & Deci, 2000);
- study goal (expected number of completed modules after 6 months), provides a clear estimation of the expectation and hence the intention of the study progress to be made;
- alcohol consumption, as it has been found to influence study progress (Singleton & Wolfson, 2009);
- life satisfaction (Diener, Emmons, Larsen, & Griffin, 1985), as more satisfaction is synergistic with better learning (Seligman, Ernst, Gillham, Reivich, & Linkins, 2009).

Analyses

As expected, the data on the dependent measure (i.e., study progress) revealed a negative binomial distribution. Because the current study concerns part-time DE, it was expected that most students would attain an average of 2 to 3 modules per year (i.e., based on data from internal year reports). Students either completed no course at all, or, had completed one, two, three or four courses. The distribution of the dependent variable was highly skewed and resembled a negative binomial distribution.

Therefore, a negative binomial generalized linear regression was conducted (i.e., using the GENLIN command in SPSS). A *P*-value below .05 was considered to be significant. A covariate model was built including all covariates, after which non-significant predictors were excluded, yielding model A. Then, model B was tested by adding the nutritional measures to model A. Univariate outliers of the variables of interest (i.e., independent variables) were excluded before analyses (i.e., a standardized *Z*-value higher than the absolute value of 3.29), in case the distribution was normal. All analyses were performed with SPSS (version 20; SPSS Inc., Chicago, IL, USA).

Results

Dataset compilation

The original dataset contained 2842 cases. Participants were excluded if they: (1) did not attempt an exam (1236 cases); (2) did not complete the survey (416 cases); (2) did not participate within 9 weeks (32 cases); or (3) made a remark at the end of the survey that led to exclusion (1 case). All exclusions mentioned led to a total of 1157 people were included in the analyses.

Descriptives

Table 1 provides an overview of the descriptives of all the variables, measured at the interval level. In Table 2 an overview of the dichotomous variables is presented. The assumption of no multicollinearity was met as the correlations between all predictors were low (i.e., below .4). This was also indicated by high tolerances (i.e., above .7: Field, 2009). All predictors (i.e., covariates and independent variables) were included in the evaluation of this assumption.

As can be seen in Table 1, the standard deviation differs among the variables, imposing a threat to the reliability of the results as homoscedasticity is an important assumption in linear models. Large differences in variances can distort the estimation of the model fit and parameters. Therefore, the variables were transformed to align the variances prior to the analyses.

TABLE 1. Descriptives of all included variables measured at interval level

Variable	Mean	SD
Study progress (successfully completed modules in 14 months)	2.49	2.56
Total work hours per week	25.80	15.97
Expected study hours per week	13.43	7.60
Age (years)	35.84	11.10
Educational level (ordinal[1])	5.90	1.38
Body mass index (kg/m^2)	23.81	4.00
Computer abilities (scale score)	42.75	5.83
Expected number of attained modules	2.24	2.34
Total weekly alcohol consumption (standard glasses)	3.50	5.46
Life satisfaction (scale score)	25.25	5.49
Caffeine consumption (mg/day)	201.44	125.44
Fish consumption (scale score, higher means more consumption)	9.71	8.22
Breakfast consumption (days/week)	6.23	1.80

[1] *Educational level is measured on an eight-level scale, ranging from low general education to post higher education.*

TABLE 2. Descriptives of all included variables measured at nominal or ordinal level

Variable	Number	Percentage
Sex		
Male	427	37.0
Female	728	63.0
Nationality		
Dutch	1039	90.0
Non-Dutch	116	10.0
Native language		
Dutch	1049	94.7
Non-Dutch	61	5.3
Study motive		
Personal	657	56.9
Professional	498	43.1

Multiple regression analyses

Chi square comparisons revealed that model A was better than the null model (i.e., an intercept only model); χ^2 (4, N = 1157) = 89.35, $p < .001$, indicating that model A fits the data significantly better than the null model. Comparison of model B with model A revealed that model B did not fit the data better, χ^2 (3, N = 1157) = 3.28, $p = .35$. This means that adding the consumption of caffeine, fish and breakfast to model A did not explain study progress better. The regression results for model A and B can be found in Table 3. Consumption of caffeine, fish and breakfast are not associated with study progress. This means that the consumption of caffeine, fish and/or breakfast are not predictive for the number of successfully completed modules after 14 months.

TABLE 3. Generalized linear regression (negative binomial) of Model A and Model B

Predictor variable	β (standardized)	Significance (p-value)
Model A (χ^2=91.530, df=5, p<0.001)		
Expected study hours	.118	<.001
Expected number of completed modules after 6 months	.153	<.001
Alcohol consumption per week	.054	.041
Life satisfaction	.091	.001
Native language[1]	.569	<.001
Model B (χ^2=94.817, df=8, p<0.001)		
Expected study hours	.123	<.001
Expected number of completed modules after 6 months	.153	<.001
Alcohol consumption per week	055	.041
Life satisfaction	.093	<.001
Native language[1]	.550	<.001
Caffeine consumption	.033	.247
Fish consumption	-.036	.208
Breakfast consumption	.019	.501

[1] *This dichotomous variable is not standardized*

Discussion

The aim of the study was to investigate the relation between the consumption of caffeine, fish and/or breakfast on the one hand and study progress on the other in adults participating in DE. Analyses revealed that the consumption of caffeine, fish and breakfast were not related with study progress, in contrast to findings in children and adolescents. This means that neither the consumption of caffeine, nor fish nor breakfast predicts the number of successfully completed modules after 14 months of studying. These results are important as the preference for DE is increasing in adults because of the flexibility it offers and because lifelong learning is important nowadays, resulting from the need for knowledge development in society and lengthening of employment age. Research in traditional education focuses on these nutritional measures. However, no research so far was focused on these relations in DE. We will discuss the results for each nutritional measure separately.

Caffeine consumption

As hypothesized, the analyses show that the consumption of caffeine was not related to study progress. The use of caffeine has been regarded beneficial for cognition (Hameleers et al., 2000; Owen et al., 2008; Ruxton, 2008), but detrimental for learning (Diamond, 2013; Owens, 2014) most likely resulting from the mediating effects of sleep processes influenced by caffeine (James et al., 2011). In addition, the benefits of caffeine on cognitive performance are disputed, considering the *withdrawal reversal* hypothesis. This makes the interpretation of the benefits or detriments of caffeine difficult. First, this could simply mean that caffeine does not impair or support learning performance. Second, since most adults in the current study have work (i.e., often a fulltime job) and family responsibilities (i.e., children and a partner), they are likely to study in the evening (as confirmed by the data; more than 70% will study in the evening on week days). This could mean that a caffeinated drink could boost performance during studying in the evening, but that the disruption of the sleep process in the following night cancels possible benefits. However, it is unlikely that many adults will use caffeine consumption as a strategy to enhance learning performance. Third, if the *withdrawal reversal* hypothesis was incorrect and cognitive benefits that translate to learning performance were following caffeine use, the caffeine consumers should have outperformed the non-users. However, this is not the case, providing indirect evidence for the *withdrawal reversal* hypothesis.

Fish consumption

Fish consumption proved to be unrelated to study progress following the analyses, in line with our hypothesis. This means that the consumption of fish – and hereby the resulting levels of n-3 LCPUFAs – is not predictive for learning performance in adults participating in DE. As discussed before, research regarding the relation between fish

consumption and learning performance in young and middle-aged adults is scarce, making these results an important addition to the body of knowledge.

Breakfast consumption

In line with our hypothesis, breakfast consumption appeared to be unrelated to study progress. This means that the number of days per week that a student eats breakfast is not predictive for one's learning performance. DE provides the students with the liberty to study whenever they want. As stated earlier, most students study in the evening during weekdays, likely resulting from work and family responsibilities. As such, direct effects of breakfast consumption will not influence their learning performance.

Strengths and limitations

The current study has multiple strengths. It is the first of its kind evaluating the relation between the consumption of caffeine, fish and breakfast on the one hand and study progress on the other in adults participating in DE. The nutritional measures are of interest in traditional education, but have not yet been investigated in another educational setting. A second aspect is that this study used a large sample providing high power and decreased the risk of contracting a type-1 error. Last, multiple possible confounders were controlled for, ruling out possible spurious relations.

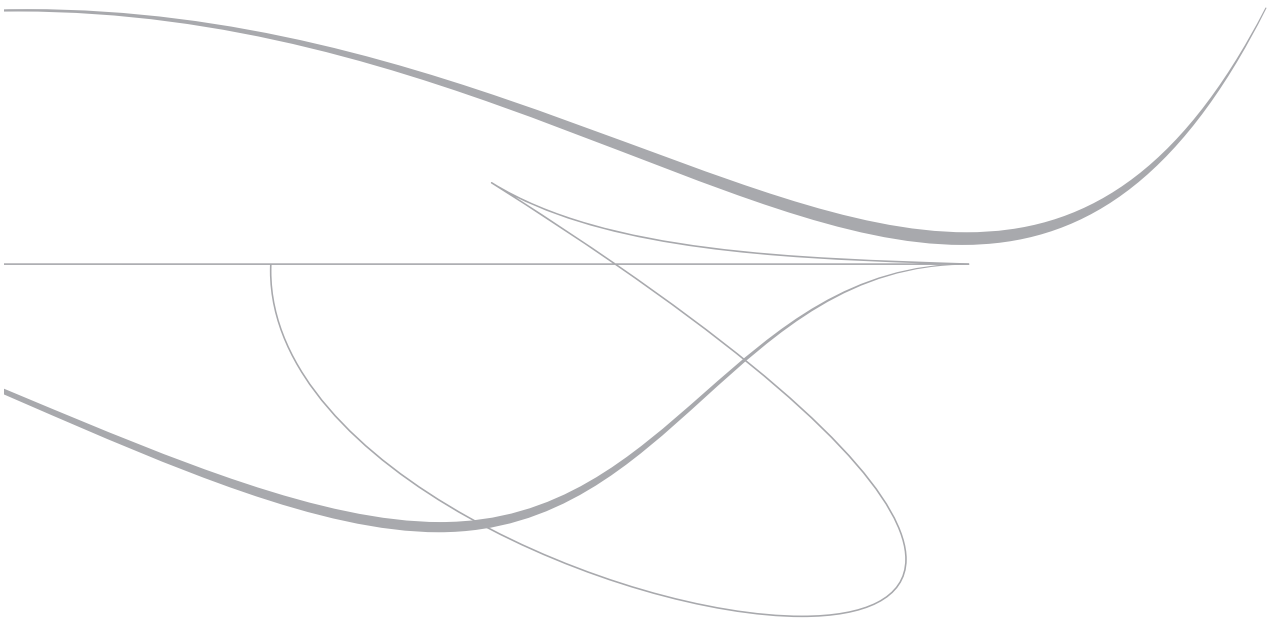
Along with these strengths there are limitations to the current study. First, these results must be interpreted with caution as its observational design does not allow for causal inferences. Second, the measurements regarding the consumption of caffeine, fish and breakfast reflect behavior around the start of the participants' study. Although dietary patterns are relatively stable throughout adulthood (Mikkilä, Räsänen, Raitakari, Pietinen, & Viikari, 2005), it is not possible to rule out changes in dietary behavior over the time period that study progress was measured. In order to expect beneficial effects in the brain following the consumption of caffeine, fish and breakfast that translate into learning and the resulting learning performance measure study progress, consistent and long-term intake is required. Third, to clean the data and prevent confounding factors, participants who did not take an official exam attempt were excluded, to correct for the large amount of zero's in the data. Excluding participants that did not officially attempted to finish a course seems to solve the problem of the redundant zero's. However, for a considerable number of courses, student attempts are not registered, meaning that despite serious attempts, only successfully finished courses will be registered. This is due to the fact that only official exams are registered, not individual assignments such as papers, for example. Thus, in excluding the excess zero's, possible true zero's were excluded as well. However, not enough information was available to make a more proper selection. Despite excluding possible 'true' students, it is unlikely that the inclusion of these students would have changed the results of the analyses considering the fact that the number of subjects remains large. Last, considering the popularity of these three nutritional measures in

traditional education, we investigated these measures in these study. As stated earlier, the nutritional palette is much more extensive than just these three measures. Other nutritional measures are also known to possibly influence learning performance (e.g., macronutrient intake: Zhang, Mckeown, Muldoon, & Tang, 2006). Therefore, it would be interesting to investigate other measures as well.

Recommendations and summary

To elaborate on the findings from the current study it is recommended that future research focuses on the causality of the relations by using an experimental design and the evaluation of possible underlying mechanisms (e.g., sleep processes when it comes to caffeine). Second, to evaluate these relations more reliably, dietary patterns must be measured repetitively to make sure intake of nutrients are stable.

To summarize, the present study showed that the consumption of caffeine, fish and breakfast do not predict study progress in adults participating in DE. This study is important as it is the first to report on these relations in this specific age group and educational setting.



CHAPTER 7

Biological lifestyle factors related to cognitive performance: Sedentary behaviour predicts processing speed

Besides genetic predisposition biological lifestyle factors (BLFs) play a role in cognitive functioning. However, research concerning the relation between physical activity, sleep and nutrition on the one hand and cognitive performance on the other hand is scarce, especially in young and middle-aged adults. Aim of this study was to examine the contribution of these BLFs to cognitive performance. Path analysis was conducted in an observational study in which 973 adults were analysed using a cross-validation approach. Participants provided information via a survey. Their cognitive performance was measured using objective cognitive tests. Exploration of all variables within each BLF regarding cognitive performance yielded a predictive cohesive model. It was shown that sedentary behaviour was positively predictive for processing speed. All other variables related to the BLFs physical activity, sleep and nutrition (i.e., physical activity, chronotype, sleep duration, sleep quality, caffeine, omega-3 and breakfast consumption) did not predict cognitive performance.

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Introduction

Cognition is highly heritable as multiple studies have shown heritability ranges from 40 to 80% (e.g., Finkel, Pedersen, McGue, & McClearn, 1995; Haworth et al., 2010). Despite this strong heritability a substantial proportion of variation in cognition is not explained by heritability. Thus, this must be explained by environmental factors. This is especially interesting as environmental factors are often controllable in contrast to genetics. The environmental part of cognition is thus influenced by individual differences that cover a broad range of characteristics among which physical activity, nutrition and sleep. These characteristics, which are defined by lifestyle, are gaining more interest recently. Maintaining a healthy lifestyle does not only result in a better physical and mental health state (Busch, Van Stel, Schrijvers, & De Leeuw, 2013), but also leads to better cognitive performance (Small et al., 2006). Research indicates that a healthy lifestyle is beneficial for cognition, as suggested by research in the domain of physical activity (PA) (e.g., Hillman, Kamijo, & Scudder, 2011), sleep (e.g. Philip et al., 2012) and nutrition (e.g., Burkhalter & Hillman, 2011). However, this research all focuses on children and adolescents and solely on separate domains or even variables within that domain (e.g., only chronotype: Vollmer, Pötsch, & Randler, 2013). Factors such as physical activity (e.g., active vs. passive behaviour), sleep (e.g., sleep duration and quality) and nutrition (e.g., breakfast and poly-unsaturated fatty acids) are biological lifestyle factors (BLFs) that influence cognition (e.g., nutrition: Burkhalter & Hillman, 2011; sleep: Dean et al., 2010; PA: Voss, Nagamatsu, Liu-Ambrose, & Kramer, 2011). However, a multi-disciplinary approach, incorporating the fields of PA, sleep and nutrition, is lacking. To our knowledge there is no research focusing on the combination of these three BLFs and the relation with cognition in young and middle-aged adults, an age group in which lifestyle habits are more stable in comparison with their younger counterparts (i.e. children and adolescents). In addition, some factors are investigated in isolation, but the combination of physical activity, sleep and nutrition is new and highly interesting as these three BLFs are, despite their unique nature, related to each other. Recently, the combination of different lifestyle factors or elements in these factors receive more attention due to the interactions that exist (e.g., Leckie et al., 2014; Van Praag, 2009). We will discuss these interactions later.

To shed more light on the environmental conditions influencing cognition, the goal of the current study was to evaluate whether the three BLFs physical activity, sleep and nutrition are predictive for cognitive performance in young and middle-aged adults using a path analysis approach. The investigation of the combined relations of BLFs with cognition provides input for new investigations into synergistic and additive effect of a healthy.

Mechanisms

Cognition is a result of the complex interactions that occur between neurons in the brain. These neurons are all interconnected with each other forming a solid network. The transfer of electrical signals and the creation and extinction, or, strengthening or weakening, of the connections that follow the electrical stimulations give rise to the full pallet of our cognitive behaviour (Kalat, 2007).

PA, sleep and nutrition are all three factors that influence the body in a biological way. They exert influence on the regulation of the body's physiological parameters. For example, the levels of brain-derived neurotropic factor (BDNF) increase when being physically active (Winter et al., 2007). BDNF is a neurotrophin that enhances the proliferation, synaptic plasticity, growth and survival of neurons (Van Praag, 2009). Sleep is regulated by melatonin, a hormone that regulates sleep onset. However, melatonin, on its turn, is regulated by light. Later bed times in these contemporary times means more light later at night, shifting the melatonin onset (Wright et al., 2013). A good example of a nutritional element influencing the body is poly-unsaturated fatty acids (PUFA's), such as omega-3, found in foods such as fish and nuts. PUFA's are important building blocks for the cells membranes, providing the proper permeability and fluidity, which is important for signal transduction in neurons (Gómez-Pinilla, 2008). In addition, they also impact directly on BDNF levels (i.e., omega-3; Van Praag, 2009).

Many of the physiological mechanisms influenced by physical activity, sleep and nutrition have implications on brain functioning and thus also possibly on cognition. For the goal of this paper, it is not of any use to provide a review of all possible mechanisms related to physical activity, sleep and nutrition and their effect on brain functioning. Readers that would like an overview of the possible mechanisms can refer to the following sources of literature for physical activity (Barenberg, Berse, & Dutke, 2011), sleep (Tononi & Cirelli, 2014) and nutrition (Gómez-Pinilla, 2008). The examples above illustrate how these BLFs influence the body biologically and especially the brain.

Cognition

Cognition is a term that is often used to refer to the mental abilities that facilitate processes such as memory, planning, inhibition and problem-solving. Cognition is a broad term that includes simple lower-order processes such as processing speed, to more complex higher-order processes such as task switching. In the cognitive domain, the executive functions (EFs) are considered to be the very important for normal adult performance. EFs are top-down controlled mental processes that are needed for concentration and attention. The use of EFs take effort, not using them means: following automatic behaviour; not changing what you are doing; and giving in to temptations (Diamond, 2013). Three EFs are described in the literature, which are based on Baddeley's model of working memory (Baddeley, 1983) and his later proposal on the functions performed by the 'central executive' (Baddeley, 1996). Miyake and colleagues (2000) described these functions as inhibition, updating, and shifting, after

statistically analysing Baddeley's proposal. To clarify, working memory can be divided into two components, short-term storage and executive processes (Smith & Jonides, 1999). The executive function updating manipulates the short-term storage and together with the storage forms the working memory.

Although processing speed is a lower-order cognitive function it is still important as many cognitive processes are dependent on processing speed. Aging causes cognitive processes to decline. Although EFs and processing speed share mutual variance, they are independently affected by age (Albinet, Boucard, Bouquet, & Audiffren, 2012). It would be interesting to account for processing speed as it can show insight in the unique age-related decline in each cognitive process.

Physical activity

There is a vast amount of research focusing on the positive effects of physical activity on cognitive processes (e.g., the review of Hillman, Erickson, & Kramer, 2008). The *executive function hypothesis* proposed a preferential benefit of physical activity for EFs (Hall, Smith, & Keele, 2001). Indeed, such differential effects of physical activity on different cognitive functions exist. EFs benefit most from physical activity, while the function processing speed seems to benefit least (Colcombe & Kramer, 2003). In their extensive review article, Barenberg, Berse, and Dutke (2011) discussed the limitations of the study of Colcombe and Kramer (2003) and investigated whether this preferential benefit of physical activity for EFs indeed was apparent. They concluded that the results point in the direction of a preferential benefit (Barenberg et al., 2011). Important to note is, that according to the three EFs (i.e., updating, shifting, inhibition) defined by Miyake et al. (2000), the function updating has never been investigated; consistent positive effects were showed on inhibition; and in the shifting domain, positive effects were found occasionally (Barenberg et al., 2011).

Opposite to physical activity is sedentary behaviour, which can be seen as part of physical activity. However, the construct sedentary behaviour is recently more and more viewed as a separate construct independent of physical activity, as a large review study found that general sedentary behaviour is not related to physical activity (Rhodes, Mark, & Temmel, 2012). This is not surprising as one can be highly physically active and still sit a large amount of the day, for example, due to a sedentary job, a very likely situation in these contemporary times. Furthermore, it is important to evaluate whether this independence also exists when relations with respect to cognitive performance are investigated. Research regarding sedentary behaviour and its relation with cognition is still very scarce, especially in young and middle-aged adults. There are some hints that low amounts of sedentary behaviour and more low-intensity behaviour could be counter-acting age-related cognitive decline and that biological mechanisms underlying sedentary behaviour and physical activity could overlap and possibly counteract their effects (Voss, Carr, Clark, & Weng, 2014). However, research is scarce and more research is needed regarding the relation of sedentary behaviour with cognition.

Sleep

Sleep deprivation leads to impaired cognitive functioning, whether the deprivation is caused by low sleep quality or simply too little sleep. At least, this accounts for children (Dewald, Meijer, Oort, Kerkhof, & Bögels, 2010), adolescents (Radek, 2013) and older adults (Nebes, Buysse, Halligan, Houck, & Monk, 2009). Sleep deprivation seems, however, to influence younger adults more than older adults (Pace-Schott & Spencer, 2011). However, this review only encompasses simple lower-order cognitive functions (e.g., reaction times on vigilance tasks). We will discuss the relation between sleep related variables (i.e., chronotype, sleep duration, sleep quality) and cognition below.

Chronotype is also called time-of-day preference and refers to a person's preference to mornings or evenings (for more information, see: Roenneberg, Wirz-Justice, & Merrow, 2003). In general, chronotype is associated with cognition, evening oriented people perform better than morning oriented people, independent of the time at which the cognitive tests were performed, as shown in a meta-analytic study (Preckel, Lipnevich, Schneider, & Roberts, 2011). Correlations between chronotype (i.e., whether this is based on sleep times or self-reported typing) and sleep duration are high (Roenneberg et al., 2003). Still, it is important to account for sleep duration as it is influenced by not only our biological clock, but also our social clock (i.e., when to get up for work). People with an evening oriented chronotype suffer more from the social clock than morning oriented people, considering the fact that most adult students have to get up early during the week for work and family responsibilities. As a result, these people build up a lack of sleep from which morning oriented people suffer less or not. In adults, ideal sleep duration is 7 to 8 hours per night. Lower as well as higher sleep duration leads to lower cognitive performance (Ferrie et al., 2011; Sternberg et al., 2013).

Although sleep quality is a heavily researched domain, research concerning cognition in adults is scarce, especially research focusing on middle-aged adults. Research in young adults shows poor sleep quality to be associated with decreased executive functioning (Benitez & Gunstad, 2012). In older adults, poor sleep quality was associated with lower cognitive functioning. The relations were, however, not uniform across different cognitive functions. Impaired sleep quality was associated with decreases in working memory and shifting, but not in processing speed (Nebes et al., 2009). Both these findings align and show that higher order executive functions appear to be more affected by sleep quality than lower order functions.

Nutrition

Recent advances in research regarding nutrition have shown that nutrition can influence cognitive functioning. Omega-3 fatty acids, for example, have gained interest by their possible role in supporting cognitive function (Gómez-Pinilla, 2008). The entire nutritional palette is too extensive to discuss, considering the goal of this article. For an overview that provides in depth information on nutrition modulating cognition and the mechanisms underlying these modulations, we refer to the article of Parletta, Milte

and Meyer (2013). We will evaluate the nutritional components that were measured in this study: caffeine; breakfast consumption; and omega-3 fatty acids.

First, caffeine can be regarded as a nutrient, a drug or a drug of abuse, depending on the way it is used (Pardo Lozano, Alvarez García, Barral Tafalla, & Farré Albaladejo, 2007). As we investigate habitual caffeine use in a healthy adult population, we will consider caffeine as a nutrient. Research shows that habitual caffeine intake is related to better long-term memory (Hameleers et al., 2000). Caffeine is often used to boost attention and concentration. A decision-making task mainly involving executive function does not benefit from caffeine after prolonged wakefulness leading to excessive sleepiness, despite reduction in sleepiness and increased psychomotor vigilance (Killgore, Grugle, & Balkin, 2012). Furthermore, consuming caffeine later in the night could also disrupt subsequent sleep processes, which could impair cognitive performance, as shown in adolescents (James, Kristjánsson, & Sigfúsdóttir, 2011). Thus, despite caffeine can boost attention and concentration, detrimental effects of sleep disturbance are possible as well.

Breakfast consumption is heavily investigated, albeit mainly in children. Breakfast is a meal that is often skipped (Mullan & Singh, 2010). Breakfast is mostly viewed as giving the body energy after a night of fasting and effects on cognition are therefore mostly viewed as direct. Theoretically, however, consuming breakfast could also have long-term benefits as a result of increased nutrient intake and better nutritional status (Pollitt & Mathews, 1998).

Research clearly points out that omega-3 fatty acids are important for normal development. However, a debate is still at hand whether omega-3 is beneficial for cognition in healthy adults (Stonehouse, 2014). A major reason for this is simply because little research is done in healthy adults as most research focuses on the development of children, adolescents and older healthy or demented adults (Luchtman & Song, 2013). Research in children, adolescents and older adults indicate that cognitive processes are enhanced following supplementation of omega-3, although more research is needed to firmly confirm this (Frensham, Bryan, & Parletta, 2012; McCann & Ames, 2005; Stonehouse, 2014),.

Biological lifestyle factor interactions

The information provided above outlines the associations that exist between the separate factors and cognition. However, the aim of this study was to elaborate on the prediction of cognition using the relations of all the factors together. Therefore, we discuss the literature that is present on moderating, mediating or even synergistic/additive effects present when combining lifestyle factors.

As stated, caffeine can impair sleeping processes and lead to daytime sleepiness (Roehrs & Roth, 2008). Short sleep duration increases food intake, and especially saturated fat intake, but it does not influence energy expenditure or basal metabolic rate (St-Onge et al., 2011). This could explain the increased risk of obesity in adults with a short sleep duration (Patel & Hu, 2008). In addition, body mass is related to lower

cognition in middle-aged adults (Cournot et al., 2006) and an increase or decrease in obesity leads to a decrease or increase in cognition, respectively (Sellbom & Gunstad, 2012). Body mass index (BMI) reflects the balance, or unbalance, that is present between food intake and physical exercise and is associated with not only cognitive functioning, but also with short sleep duration.

A cross-sectional study investigating the relation between sleep timing and physical activity indicates that later sleep schedules are related to less physical activity and more sedentary behaviour. In addition, chronotype appears to be related to physical activity as well, despite that this relation does not reach significance, likely due to the small sample size (N=22) (Shechter & St-Onge, 2014). This is not surprising, since although sleep schedule and chronotype are highly related, sleep schedule is also dictated by the social clock while chronotype is only dictated by the biological circadian clock.

A study investigating the relation between physical activity and cognitive function and whether a dependency with omega-3 existed, found interesting results. It appeared that higher omega-3 levels corrected the deleterious effects of lower physical activity. It is hypothesized that this is possible as biological effects for both omega-3 and physical activity are overlapping. However, there was no additive effect when levels of both omega-3 and physical activity were high (Leckie et al., 2014). This provides a clear moderation effect of omega-3 on the relation between physical activity and cognition. A large cross-sectional study among middle-aged adults shows that breakfast skipping is associated with less physical activity (Wyatt et al., 2002). However, this study was observational meaning that it is not possible to conclude whether breakfast skipping was causing less physical activity or vice versa. Possible confounding is very likely (i.e., breakfast skipping is associated with other unhealthy behaviours). Further, a clear relation that is well documented is the relation between TV viewing and BMI, more TV viewing seems to lead to a higher BMI (Rhodes et al., 2012).

The present study

In the present study, we examined whether the BLFs physical activity, sleep and nutrition were related to cognitive performance. Specifically, the goal was to integrate the different variables within the three BLFs domains in one model predicting cognitive performance. The study was executed among young and middle-aged adult students of the Open University of the Netherlands (OUNL), a formal university-level institute providing distance education. The aim of this study was to provide more insight in the contribution of individual environmental factors (i.e., BLFs) to cognitive performance. Path analysis was used to investigate the relations. As research in this adult population regarding BLFs and cognitive performance is scarce, a cross-validation approach was used with an *exploratory* and *confirmatory mode*. The *exploratory* mode was used for model development, while the *confirmatory* mode was used for validation of the developed model.

Methods

Design

Data from this observational study come from the Adult Learning Open University Determinants (ALOUD) study. The ALOUD study is an investigation of different psychological and biological factors possibly affecting cognition and/or study progress in students participating in distance education. Collected measures in the ALOUD study not included in this article were psychological factors and study progress. All variables within the BLFs were reported via an online digital survey, which was conducted after registration at the university. Cognitive performance was measured objectively using digital cognitive tests conducted via the participants' computer directly after the survey.

Participants

During 1 year (Sept. 2012 – Aug. 2013), all new students of the OUNL who signed up for one or more regular bachelor or master course(s) were invited to participate. At the OUNL, students can register and start throughout the year as the education is modular and self-paced, open to everyone (with an age of at least 18 years old), and the curriculum is not fixed. The OUNL mainly delivers online education. The approached population size was 4945, 57.5% of those approached responded (N=2842) and 41.27% of those approached (N=2041) fully participated.

Procedures

Participants were invited automatically via the e-mail system of the university 14-21 days after successful registration. The seven days range is because a bulk mailing was sent weekly. Students received a reminder two weeks after the initial invitation and one week later a last reminder by e-mail. Four weeks after the initial invitation, a phone call was made (it was tried to reach participants in the three subsequent weeks) in which potential participants were asked whether they were still interested in participating. If so, they received the original invitation once more when needed and a reminder 6.5 weeks after the initial invitation, which was around 1.5 weeks after the phone call. In case the phone call was made in week 6, the reminder was sent one week later. Participants only received reminders or a telephone call if no full response was recorded.

The survey was administered online using LimeSurvey®, version 1.92+ (LimeSurvey Project Team / Carsten Schmitz, 2012). Full participation cost the participants 45 to 60 minutes on average and it was possible to stop and continue later, allowing participants more freedom in their participation by spreading the time burden. Participants who fully participated could win (5% chance) a gift voucher of €20. The ALOUD study was ethically approved by the local ethical committee of the OUNL. Each participant signed a digital informed consent form, explicating the use of the personal data gathered, voluntary participation, possibility to withdraw at any time, and finally

giving their permission to use the data for the described goals. Participants had to click a check-box to agree with the terms mentioned; a mandatory action to start the survey.

Materials

Outcome measures

Cognition was measured by an online digital cognitive test battery. Three tests were administered: (1) the Trail Making Test (TMT) (Army Individual Test Battery, 1944); (2) the Substitution Test (ST), which resembles the symbol digit modalities test (Smith, 1991); (3) and the N-back task (NBT) (Lezak, Howieson, & Loring, 2004). The TMT resulted in a measure for the executive function shifting, measured via the B-A part. The outcome measure in the ST was the number of items correctly substituted in 90 seconds, which is a measure of information processing speed. In the NBT the number of correctly remembered items is a measure for working memory and the executive function updating. Taken together, the outcome measures included for the participants' cognitive performance were two measures: executive functioning and processing speed. Executive functioning was operationalized as an accumulated score of the standardized scores for shifting and updating.

Predictors

The measures for the variables within each BLF were extracted from various questionnaires. *Physical activity* was measured via the Short Questionnaire to ASsess Health-enhancing physical activity (SQUASH), which has a reasonable reliability (r = .58) and validity (r = .45) (Wendel-Vos, Schuit, Saris, & Kromhout, 2003). Physical activity was calculated as a weekly activity score; an accumulated product score of intensity of the activity multiplied by the minutes spent on the activity. *Sedentary behaviour* was measured using a self-developed questionnaire based on the principle of the SQUASH. Questions on sedentary behaviour concerned sedentary behaviour during work, transportation, leisure time (i.e., on work and free days), resting, and sleeping. Sedentary behaviour was calculated as a total score of minutes of sitting, lying and sleeping per week. *Chronotype* was measured via reported sleep- and wake-times on work and free days using specific questions from the Munich ChronoType Questionnaire (MCTQ) (Roenneberg et al., 2003). Midsleep on free days corrected for sleep debt (MSFSC; see section 1.4), was used as the measure for chronotype (Roenneberg et al., 2004). *Sleep quality* was measured with the Pittsburg Sleep Quality Index (PSQI), a well-known and well-validated self-report sleep quality measure (Buysse, Reynolds, Monk, Berman, & Kupfer, 1989). The global PSQI score was used as the measure for sleep quality. *Sleep duration* was derived from the PSQI and was included as a polynomial term as an inverted U-shape is present in the relation with cognition. *Breakfast consumption* was measured as a number of days per week that the participants consumed breakfast. *Caffeine* was measured as average daily caffeine consumption calculated from reported coffee, tea and energy drink consumption using average beverage caffeine values reported in the literature (Ruxton, 2008).

Omega-3 was measured with a questionnaire validated against omega-3 plasma levels (De Groot, Van Boxtel, Schiepers, Hornstra, & Jolles, 2009).

Covariates

Next to the three BLFs discussed above, five covariates were taken into account:

- alcohol use, as it was positively related to cognitive performance in an observational study conducted among middle-aged adults (average age of 56) (Kalmijn, Van Boxtel, Verschuren, Jolles, & Launer, 2002). However, another study among younger middle-aged adults (average age of 43) found no associations between alcohol use and cognitive performance (Caspers, Arndt, Yucuis, McKirgan, & Spinks, 2010).
- educational level (measured on an eight-level scale), as it is a predictor for cognitive performance (Van der Elst, Van Boxtel, Van Breukelen, & Jolles, 2006a; Van der Elst, Van Boxtel, Van Breukelen, & Jolles, 2006b; Van der Elst, Van Boxtel, Van Breukelen, & Jolles, 2006c). In addition, educational level is associated with different lifestyle elements. For example, a higher educational level is related to higher levels of physical activity (Droomers, 2001) and predictive for a healthier nutritional pattern (Darmon & Drewnowski, 2008).
- age, as it is an important predictor for cognition as well, as cognitive functions decrease with age (Albinet et al., 2012).
- body mass index (BMI; computed from self-reported weight and height), as it is an important covariate since these three BLFs are associated with BMI. For example, low sleep duration is associated with increased BMI (Taheri, Lin, Austin, Young, & Mignot, 2004).
- computer abilities (measured via a self-developed questionnaire mapping attitude, confidence, and skills towards the use of a computer), as the cognitive tests were conducted via the participants' computer. This could mean that people with lower levels of computer abilities had lower consecutive performance levels. However, this should only be visible in the processing speed measure as the executive measures correct for basic performance (i.e., processes that are not of interest such as motor speed, visual performance, etc.). However, in the substitution test, no correction for basic performance was possible.

Analyses

Pre-processing and the analyses for descriptives were done in SPSS (version 20; SPSS Inc., Chicago, IL, USA). Path analysis was executed using structural equation modelling (i.e., with only manifest variables) performed in AMOS version 22.0.0 (Arbuckle, 2012). Cross-validation was conducted as follows: The final sample was randomly split in two subsamples, with an almost equal number of cases. One subsample was used as a *testing* sample to develop a model based upon theory and using an *exploratory* mode. The second subsample was used as a *validation* sample to test the developed model in a *confirmatory* mode, to check the validity of the developed model.

For each lifestyle factor a separate model was build, based upon theory discussed in the introduction. Subsequently, the model fit was evaluated by investigating fit and modification indices using the *testing* subsample. When the fit indices demonstrated proper fit, the statistically non-significant parameters were trimmed (i.e., *P*-value higher than .05). The parameter with the highest *P*-value was excluded in a step-by-step mode, re-evaluating the model at each step. This finally yielded one model for each lifestyle factor. The last step was to combine each of the three final models in one model and add inter-factor relations to the final model after which it was evaluated on fit. Finally, this model was tested using the *validation* dataset, in order to evaluate the validity of the final model.

The fit measures reported are the: Tucker-Lewis coefficient (TLI; Bollen, 1989), comparative fit index (CFI: Bentler, 1990), root mean square error of approximation (RMSEA: Browne & Cudeck, 1992) and standardized root mean square residual (SRMR: Byrne, 2010). Proper fit is indicated when: TLI and CFI are higher or close to .95, RMSEA <.06 and SRMR <.08 (Hu & Bentler, 1999). Univariate outliers were excluded before analyses (i.e., a standardized *Z*-value higher than the absolute value of 3.29) in case the distribution was normal. Multivariate outliers were inspected after model inspection and excluded when needed.

Results

Dataset compilation

The original dataset contained 2842 cases. Participants were excluded if they: (1) did not complete the survey and the cognitive tests (1224 cases); (2) made a remark at the end of the survey that led to exclusion (47 cases); (3) had missing data (455 cases); (4) performed below chance level on the NBT (47 cases); and (5) outliers were excluded as mentioned in the methods section (96 cases). All exclusions mentioned led to the analyses reported below with 973 people included. This file was then randomly split in a *testing* sample (N=486) and a *validation* sample (N=487) for cross-validation.

Descriptives

Each model was tested using the method of asymptotically distribution free (ADF) estimation to correct for non-normality, as kurtosis values should be around 1 and multivariate kurtosis should not be higher than 5 (Byrne, 2010), which was not the case. Furthermore, the distribution of the outcome measure executive functioning was not normal. ADF should only be employed when the sample size is greater than 10 times the number of freely estimated parameters (Byrne, 2010), which was the case. Because ADF estimation does not require normality, possible present multivariate outliers did not have to be excluded.

The descriptives are depicted in Table 1. The assumption of no multicollinearity was met, following inspection of the correlations (i.e., below .8, data not shown,

according to Field, 2009). All variables were included in the evaluation of this assumption. As can be seen in Table 1, the standard deviation differs among the variables, imposing a threat to the reliability of the results as homoscedasticity is an important assumption in linear models. Large differences in variances can distort the estimation of the model fit and parameters. Therefore, the variables were transformed to align the variances prior to the analyses. In addition, to make sure the *testing* and the *validation* sample were not too different from one another, variances were tested on equality using Levene's test. This indicated no difference (data not shown). All descriptives mentioned in Table 1 were executed over the entire dataset, before random splitting.

TABLE 1. Descriptives of all included variables

Variable	Mean	SD
Processing speed (test score)	50.36	7.55
Executive functioning (compound score)	0.00	1.61
Educational level (ordinal)	5.96	1.37
Age (years)	36.86	10.10
Body mass index (kg/m^2)	24.21	3.64
Computer abilities (scale score, higher is better ability)	43.42	5.48
Total weekly alcohol consumption (standard glasses)	2.94	4.11
Physical activity per week (intensity score)	7629.85	3501.44
Sedentary behaviour per week (minutes)	6417.07	1332.04
Sleep quality score (scale score, higher is lower quality)	5.96	1.70
Sleep duration (hours)[1]	7.95	0.95
Chronotype (midsleep on free days, corrected for sleep debt)	3.83	0.91
Breakfast consumption (days per week)	6.19	1.86
Caffeine consumption (mg/day)	316.46	181.67
Omega-3 (scale score, higher is more omega-3)	9.53	6.70 1

[1] *Despite a polynomial term is used in the analysis for sleep duration, the original mean and SD are depicted for interpretation purposes*.

Path analyses

For each BLF a model was created based upon theory. Model 1 depicts the BLF physical activity (Figure 1), model 2 depicts the BLF sleep (Figure 2) and model 3 depicts the BLF nutrition (Figure 3). The analyses of the three structural models showed the models fitted the data properly as indicated by the fit indices (Table 2). The only exception is that for model 1 and 2 the TLI is too low. However, since the TLI accounts heavily for model complexity, this follows logically from the models. Taking into account the explorative nature in this step of model development, these values are not necessarily negative as all other fit indices are indicating proper fit. After trimming non-significant parameters, TLI increases dramatically, as shown later. Modification indices (threshold = 4) were not displayed, indicating no modification was needed, which was in line with the fit indices, indicating proper fit.

TABLE 2. Fit indices for the full path models

Model number	TLI	CFI	RMSEA	SRMR
1	.793	.980	.056	.0214
2	.812	.971	.055	.0295
3	.967	.997	.025	.0157

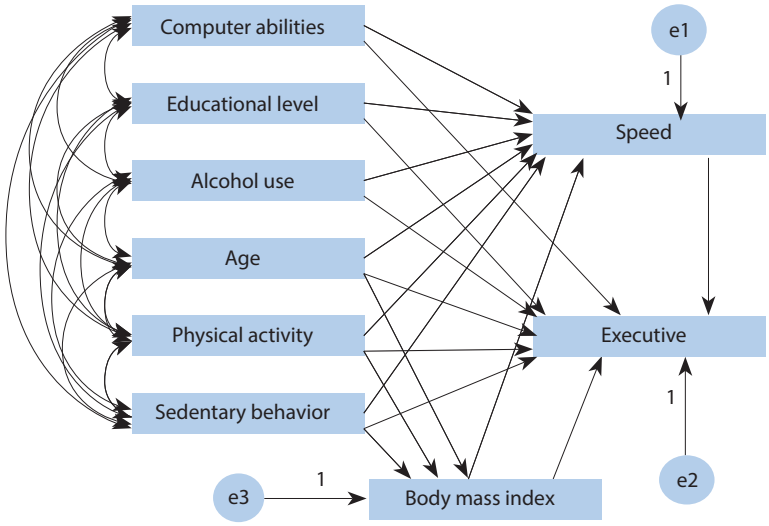

FIGURE 1. Model 1: Full model for the BLF physical activity

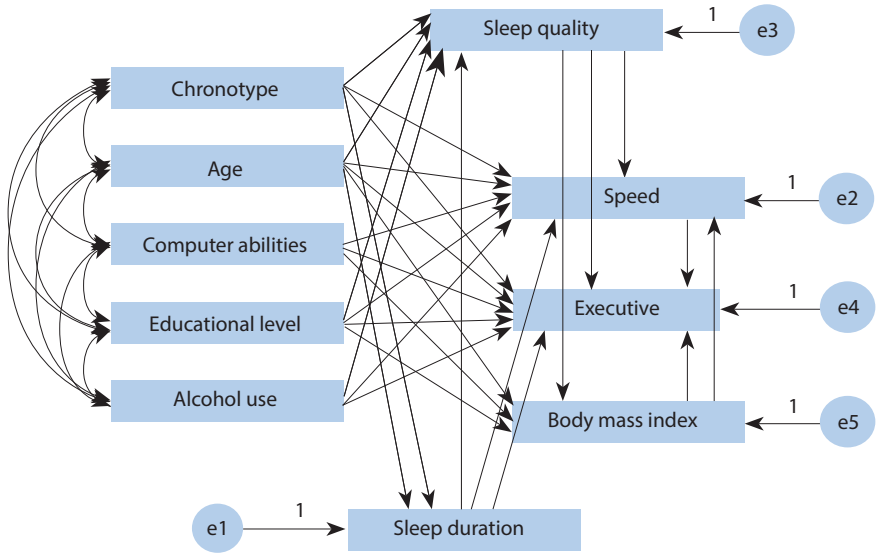

FIGURE 2. Model 2: Full model for the BLF sleep

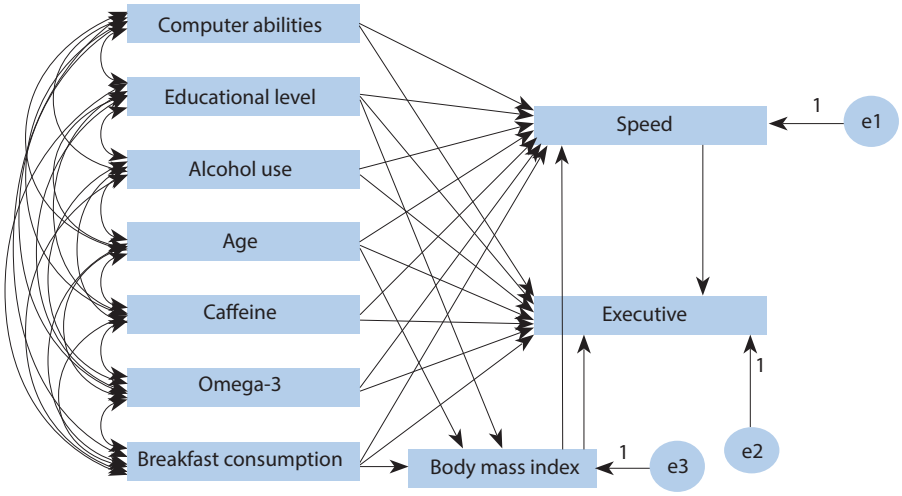

FIGURE 3. Model 3: Full model for the BLF nutrition

The next step was to trim the non-significant parameters. This resulted in model 4 for the BLF physical activity (Figure 4), model 5 for the BLF sleep (Figure 5) and model 6 for the BLF nutrition (Figure 6). All trimmed models fitted the data very good as indicated by the fit indices reported in Table 3. All three figures are displayed with their parameter's covariance, regression, or explained variance estimates. Trimming the models revealed only sedentary behaviour to be a relevant predictor of all the BLF variables. The trimmed down model for the BLF sleep showed the same model as the trimmed down model for physical activity without sedentary behaviour. There was, however, a difference for the trimmed down model nutrition. Here, alcohol use remained a significant predictor despite the fact that this predictor did not remain significant in the other two trimmed models (i.e., model 4 and 5). In model 4, exclusion of sedentary behaviour indicated that 0.9% of the variance was explained by sedentary behaviour.

TABLE 3. Fit indices for the trimmed path models

Model number	TLI	CFI	RMSEA	SRMR
4	1.033	1	.000	.0187
5	1.024	1	.000	.0158
6	1.004	1	.000	.0382

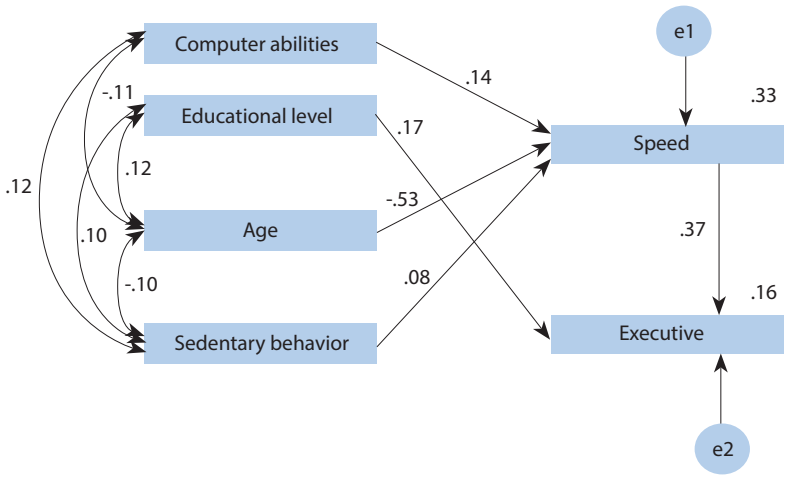

FIGURE 4. Model 4: Final model for the BLF PA after trimming model 1

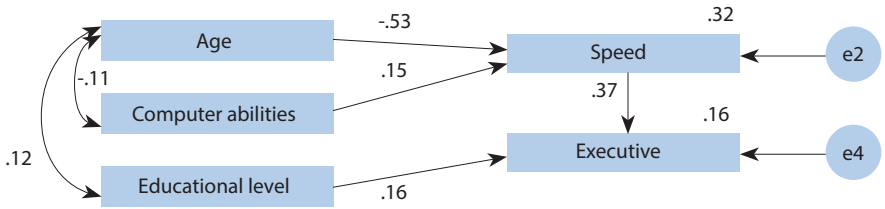

FIGURE 5. Model 5: Final model for the BLF sleep after trimming model 2

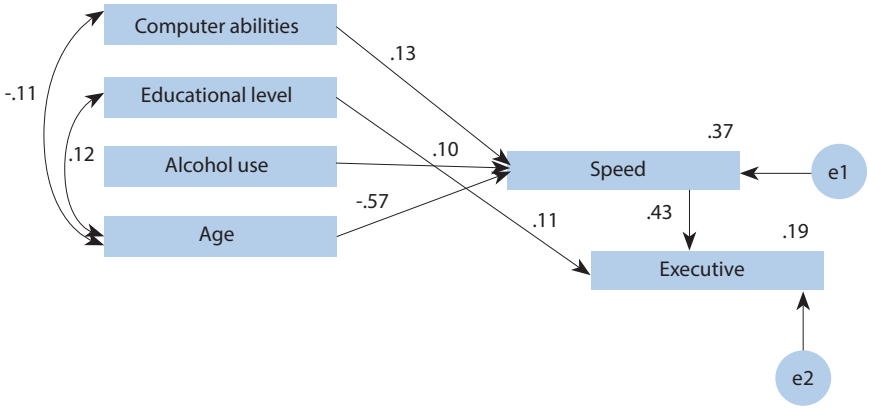

FIGURE 6. Model 6: Final model for the BLF nutrition after trimming model 3

The next step was integration of the three models into one integrated model. Model 7 displays the start model of the integrated model in which models 4, 5 and 6 are integrated (Figure 7). Trimming the insignificant parameters in this model led to model 8 (Figure 8), which is displayed with its parameter estimates. Both model 7 and 8 showed proper fit (Table 4). All estimates related to model 8 can be found in Table 5.

TABLE 4. Fit indices for the final path models

Model number	TLI	CFI	RMSEA	SRMR
7	1.004	1	.000	.0313
8	1.003	1	.000	.0187
Validation	1.042	1	.000	.0132

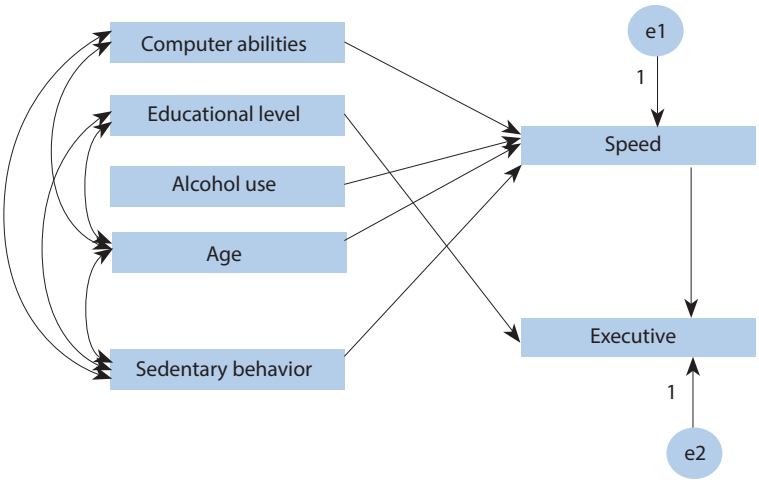

FIGURE 7. Model 7: Integrated model for all BLFs

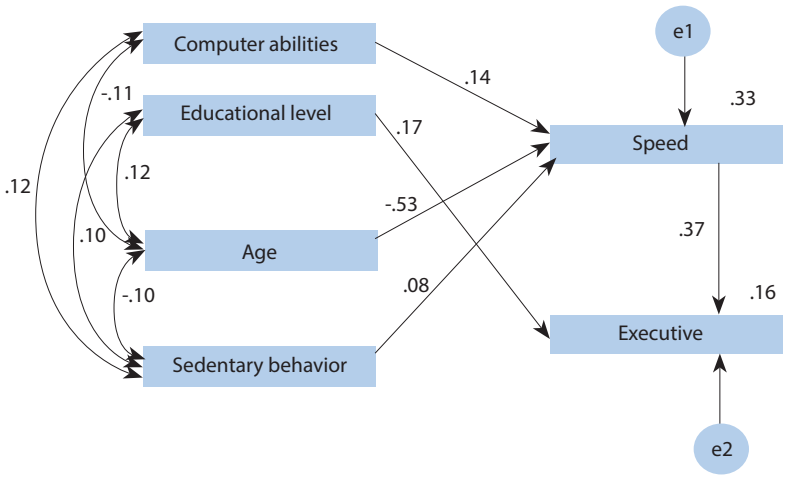

FIGURE 8. Model 8: Final model for all BLFs after trimming model 7

The next step was to execute the cross-validation and test model 8 with the validation sample. Validation of the developed model indicated the model was fitting the data properly as indicated by the fit indices (Table 4). All fit indices are perfectly within the limits of proper fit indication. Inspection of the estimates shows three covariances to be insignificant, these are displayed in grey. The parameter estimates differ a little from the estimates in model 8, but are very comparable (Table 5). In the validation step, exclusion of sedentary behaviour indicated that 0.9% of the variance was explained by sedentary behaviour. This *confirmatory* step in the cross-validation procedure means the model developed in the *exploratory* mode is correct.

TABLE 5. Estimates for model 8 and the validation model

Estimated parameter	Estimate	*P*-value
Model 8		
Regression weight		
Sedentary behaviour --> Speed	.080	.022
Computer abilities --> Speed	.142	<.001
Age --> Speed	-.525	<.001
Education --> Executive	.169	<.001
Speed --> Executive	.373	<.001
Correlation		
Sedentary behaviour <--> Age	-.103	.019
Sedentary behaviour <--> Education	.097	.035
Age <--> Education	.116	.010
Age <--> Computer abilities	-.112	.012
Sedentary behaviour <--> Computer abilities	.121	.007
Variance		
Sedentary behaviour	2.509	<.001
Age	1.135	<.001
Education	1.908	<.001
Computer abilities	2.592	<.001
e1	2.425	<.001
e2	2.073	<.001
Squared multiple correlation		
Speed	.331	-
Executive	.161	-
Validation model		
Regression weight		
Sedentary behaviour --> Speed	.100	.006
Computer abilities --> Speed	.163	<.001
Age --> Speed	-.580	<.001
Education --> Executive	.120	.003
Speed --> Executive	.408	<.001
Correlation		
Sedentary behaviour <--> Age	-.017	.715
Sedentary behaviour <--> Education	.030	.509
Age <--> Education	.128	.003
Age <--> Computer abilities	-.063	.158
Sedentary behaviour <--> Computer abilities	.158	<.001
Variance		
Sedentary behaviour	2.459	<.001
Age	1.393	<.001
Education	1.840	<.001
Computer abilities	2.301	<.001
e1	2.139	<.001
e2	2.089	<.001
Squared multiple correlation		
Speed	.392	-
Executive	.174	-

Note: Regression weights are standardized

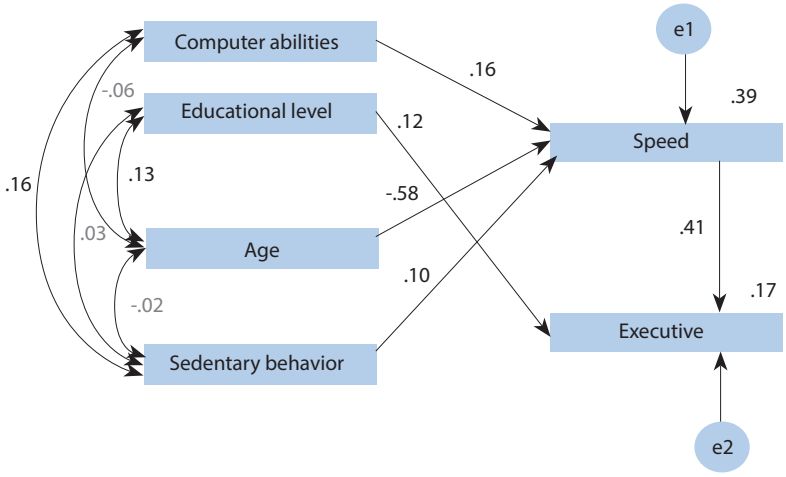

FIGURE 9. Validation model: Validation of the developed model (model 8)

Discussion

The goal of the present study was to examine whether the BLFs physical activity, sleep and nutrition were related to cognitive performance in adults. Specifically, the goal was to integrate the different variables within the three BLFs domains in one model predicting cognitive performance. Model development revealed that within the BLF physical activity a model emerged after *exploratory* analyses in which sedentary behaviour remained a positive predictor for processing speed (see Figure 4). Within processing speed 0.9% of the variance was explained by sedentary behaviour. Physical activity was trimmed out of the model, meaning that it did not predict either speed or executive function. This was not expected, as earlier research showed physical activity to be differentially related to specific cognitive functions (Barenberg et al., 2011; Colcombe & Kramer, 2003; Hillman et al., 2008). However, as the executive function measure represented score on a shifting and updating task, this could explain these findings. Barenberg et al. (2011) reported that the function updating was never investigated and that the results on the function shifting were mixed. Hence, these findings are interesting as this is probably the first study including an updating executive function measure regarding physical activity. The finding that sedentary behaviour was positively predictive for processing speed is an unexpected one. The measurement of specific types of sedentary behaviour is more and more recommended (Rhodes et al., 2012), as research showed that different types of sedentary behaviour (e.g., watching TV vs. working on the computer) are differentially associated with cognition (Kesse-Guyot et al., 2012). For example, Kesse-Guyot et al., (2012) showed TV viewing to be negatively related to cognitive functioning, while computer use was positively related to cognitive functioning. The population

investigated in the current study is characterized by fulltime working adult students, who often have very limited time to study, not only because of work responsibilities, but very often also because of family responsibilities (e.g., children, partner). It is therefore very likely that the sedentary time here reflects more of the sedentary time caused by positive sedentary behaviours (e.g. studying) that stimulates the brain, than negative sedentary behaviours (e.g. TV viewing), since overall sedentary time was measured.

Model development of the BLF sleep did not reveal any significant relation between any variables within the BLF and cognitive performance. This was unexpected as the model was clearly based upon theory. Although there were relations among the sleep variables themselves, neither sleep duration, nor sleep quality or chronotype did predict cognitive performance. Since the aim was to predict cognitive performance, all predictors not related to cognitive performance were trimmed, leading to all sleep related variables being omitted from the final model. These findings were unexpected as literature suggests all three variables to be related with cognition. No direct explanation for these findings was apparent in the literature. Therefore, we will discuss some relevant literature and try to provide explanations. First of all, when it comes to chronotype, Preckel et al. (2011) showed in their meta-analyses chronotype to be related to cognitive performance, however, this finding was concluded from research in adolescents/young adults (average age range=15.19-25.04). In addition, chronotype was in this study defined as a two-dimensional construct. Furthermore, cognition was measured using various different aggregated tests. In the current study, participants age range was different (18.37-68.86 years) and chronotype was defined as a continuous variable (i.e., midsleep on free days corrected for sleep debt; Roenneberg et al., 2004). Cognitive performance was measured for two specific constructs, no overall cognitive scores were used. Taken together, these differences can explain the different findings: it could well be that at older ages, chronotype is not that strongly related anymore to cognitive performance. In addition, our use of a continuous chronotype measure ensured better estimation of chronotype, so a possible relation with cognitive performance should have stood out if present. Further, it could be that other cognitive functions are associated with chronotype, but not processing speed and executive functioning. Second, sleep duration was also not predictive for cognitive performance. Sleep duration was included as a polynomial term, since research shows an inverted U-shaped relation with cognitive performance (Ferrie et al., 2011; Sternberg et al., 2013). Sleep duration being not predictive was unexpected, considering the fact that these previous studies were executed in adults. However, the cognitive tests executed in the previous research mentioned included different tests measuring an aggregated set of cognitive functions (Ferrie et al., 2011; Sternberg et al., 2013). This could mean that sleep duration is not, or not strongly enough, associated with executive function or processing speed, but that it is associated with combined cognitive processes. Third, sleep quality did not show to be predictive for cognitive performance, partly opposed to the expectations from literature. Sleep quality not

being related to processing speed is in accordance with the literature (Nebes et al., 2009). Sleep quality not being related to executive functioning was unexpected as research suggests a relation (Benitez & Gunstad, 2012; Nebes et al., 2009). However, sleep quality is barely investigated in especially middle-aged adults. It could be that no relation between sleep quality and executive functioning exists at this age.

For the BLF nutrition, the model was based upon theory, although there were less indirect paths and more covariances assumed compared to the other two models, as research in this area is not so developed. In trimming this model, none of the variables within the BLF nutrition proved to be significantly related with cognitive performance. This was less surprising as the three variables caffeine, omega-3 and breakfast investigated here, were measured on a habitual use level. First, for caffeine, this means habitual use is not predictive for cognitive performance. As shown by Killgore et al. (2012), executive functioning is not influenced by caffeine use. These findings are in line with the research conducted previously. In addition, Ruxton (2008) shows in an extensive review that caffeine is expected to have short-term effects on cognition. Since timing of cognitive testing and specific consumption of caffeine use prior to timing was not investigated in the current study, this cannot be evaluated here. Lastly, tolerance effects of caffeine are subject to debate and no agreement is apparent on whether caffeine actually stimulates cognition, or just restores it after tolerance effects appear (Ruxton, 2008). Second, omega-3 did not show to be a significant predictor for cognitive performance in adults, a relation which is still under debate in the literature (Stonehouse, 2014). Therefore, we conclude that omega-3 does not predict cognitive performance in young and middle-aged adults. Last, breakfast consumption did not predict cognitive performance. Breakfast consumption mostly provides direct effects on cognition (i.e., in the morning, after consumption). Considering that most adults in the current study have full-time jobs and family responsibilities (i.e.,. children and a partner), they will most likely study in evening hours (as confirmed by our data; more than 70% will study at night on week days and more than 60% in the morning and/or afternoon in the weekend). Therefore, it is understandable that breakfast consumption did not predict cognitive performance. In addition, the general belief that breakfast is 'the most important meal of the day', seems to be far-fetched as this review shows that there is no general 'recipe' for breakfast in relation to cognition (Zilberter & Zilberter, 2013). For both caffeine and breakfast consumption there seemed to be no case of direct influence, more a literature suggested direction and therefore assumed relation. Together, the above discussed findings lead us to conclude that no relation for each of these variables is apparent with cognitive performance.

Regarding the covariates, in all trimmed models computer abilities and age had the same relation with performance on the cognitive function processing speed. Together, they predicted 32.2% of the variance in the cognitive function processing speed (see Figure 5). Most of this predicted variance was explained by age, which is in accordance with the literature (Albinet et al., 2012). Still, computer abilities have a reasonable portion in the explained variance of processing speed, as expected.

Furthermore, in line with our expectations (see section 2.4.3), computer abilities did not predict executive performance. A positive relation between processing speed and executive function was apparent, as indicated by earlier research (Albinet et al., 2012). Educational level is positively related to executive functioning in all trimmed models, which is in line with previous research (Van der Elst et al., 2006a, 2006b). The negative covariance between age and computer abilities means that a higher age is associated with lower computer ability. This is explainable as older people often encounter more difficulties with computers. However, the magnitude of the correlation indicates the correlation is quite low. The positive covariance between educational level and age is fairly logical, as older ages had more possibilities to attain a higher degree than their younger counterparts. Model 6 shows alcohol use to be a significant covariate, which is not apparent in model 4 or 5. In model 4, alcohol use remains a positive predictor for processing speed, which was not expected. We will discuss this further below. Last, in model 4, sedentary behaviour showed to be positively correlated with computer abilities and educational level, and negatively correlated with age. The correlation with computer abilities indicated that more sitting time is associated with better computer ability. This can be explained as people who work more with a computer are likely to sit more. The correlation with educational level indicated that people who sit more are likely to have a higher educational level, which can be explained by the fact that higher educated people are more likely to have a desk job compared with lower educated people. As a result of the desk job, these people tend to sit more during the day. The negative correlation with age indicates that older people tend to sit less, which is a finding that is difficult to explain.

Next step was to integrate the three developed models (model 4, 5 and 6) in one final model predicting cognitive performance. Reviewing these three models leads us to conclude that only model 4 contained a predictor of interest. Therefore, this model could be used as the final model. However, since there was a difference in the remaining covariates in model 6, compared to the other two models (i.e., model 4 and 5), a new model was created which was based upon model 4, with the inclusion of alcohol use (Figure 7). As could be expected, trimming of insignificant parameters led to the same model as model 4 (Figure 8). This was the final integrated model.

Ultimately, we validated the final integrated model (see Figure 9). The validation of the developed integrated model showed the model to be correct as the fit measures indicated good fit (Table 4). This indicated the developed model is generalizable to the population, and that the conclusions with regard to sedentary behaviour is correct. Model inspection regarding the estimates of the parameters showed that three significant covariances from the integrated model with the *testing* data (Figure 8) were not significant with the *validation* data (Figure 9). This led us to conclude that in the end, computer abilities and age were not correlated, as well as educational level and sedentary behaviour, and, age and sedentary behaviour. However, despite these covariances being different from model 8, the depicted paths in the model still holds, as indicated by the fit measures (Table 4). The validation of model 8 explains even

more variance in both the measure of processing speed and executive functioning. Most important to note is that sedentary behaviour explained 0.9% of the variance in the cognitive function processing speed in both the *testing* data as well as the *validation* data.

Important limitations in the current study were: First, the study is observational and does not allow for causal inferences, although the hypotheses were theory-driven and path analysis assumes directional paths implying causation. Second, the cognitive tests were conducted at the participants' home after the survey that lasted around 45 minutes. Although participants were instructed to conduct the cognitive tests in a well-rested and active state and without possible distraction, and they had the liberty to postpone the test and thus separate it from the survey, it could well be that participants did the tests directly after the survey, when they were probably already fatigued by the survey. Alternatively, they might have been distracted by their surrounding (e.g., a pet, child or partner). However, both last points were tackled by the large data set largely smoothing these possibly confounding factors. Third, survey based research is in many cases not the most reliable type of research, not only because of social desirability, but also because some self-report measures may be debatable in terms of reliability (e.g., physical activity: Slootmaker, Schuit, Chinapaw, Seidell, & Van Mechelen, 2009), although these authors claim that in adults the reliability is acceptable.

The strengths of this study are multiple. The large data set provides a high power related to the findings and decreases the risk of contracting a type-1 error. However, since *explorative* model development increases capitalization on chance, a cross-validation approach was used to correct for this. This approach led us safely to conclude that the model was generalizable to the population. Another strength is that this adult population has rarely been investigated, making these new findings an important starting point for the fields of cognition and individual differences in normal adult age. Further, investigating the combination of these three BLFs physical activity, sleep and nutrition is a new and challenging approach, providing new insights. Last, a major strength is that a number of possible confounders was controlled for, eliminating possible spurious relationships.

Considering these strengths and limitations we suggest future research to investigate the relations between BLFs and their respective relation with, or effect on, cognition as this will create a better understanding of the environmental influences on cognition. Last, the results presented here indicate that sedentary behaviour predicts processing speed in young and middle-aged adults. All other BLF variables do not predict cognitive performance. Except for sedentary behaviour, the investigated differences in lifestyle do not seem to contribute to the variation in cognitive performance. These results should not promote people to be more sedentary as it is not clear which exact sedentary behaviours are responsible for this effect and research shows sedentary behaviours to be differently associated with cognition (Kesse-Guyot et al., 2012; Rhodes et al., 2012). Therefore these results should be interpreted with care and more research is needed to clarify this relation.

Conclusion

Research shows the BLFs physical activity, sleep and nutrition to contribute to cognitive performance. However, research has not yet focused on a multidisciplinary approach with respect to these BLFs in relation to cognitive performance in young and middle-aged adults, where lifestyle habits are more stable. The current study tried to shed light on the shared contribution different variables within the BLFs physical activity, sleep and nutrition have on cognitive performance. To summarize, it seems that only sedentary behaviour predicts processing speed in young and middle-aged adults. This means that physical activity and the variables within the BLFs sleep and nutrition may not have such a large impact in adults, in comparison with children or adolescents. The investigated individual differences in lifestyle do not seem to contribute to the variation in cognitive performance. It is not advised to be more sedentary as it is not clear which specific sedentary behaviour is the source of this relation and whether it really is sedentary behaviour causing this relation and not a confounding factor.

CHAPTER 8

General discussion

The aim of this dissertation was to explore the characteristics of different student groups (i.e., successful, non-successful, and non-starting). The second aim was to examine whether biological lifestyle factors (BLFs) predicted learning performance. Third, it aimed to investigate whether the BLFs predicted cognitive performance, as this can be a predictor for learning in traditional education. The final aim was to determine whether a possible relation between the BLFs and learning performance was mediated by executive functions (EFs).

This investigation was part of the Adult Learning Open University Determinants (ALOUD) study where adults participating in distance education (DE) are studied. First, the general research findings and outline of this dissertation is briefly considered. Then, the relation between the findings of this dissertation and the general body of research and knowledge is discussed as well as the general strengths and limitations of the project. Last, the implications of this dissertation on the relevant domains in research and educational practice are explored.

Dissertation overview and main findings

Chapter 1 provides a general introduction to this dissertation, while chapter 2 provides an overview of the design of the entire ALOUD project. The study conducted in chapter 3 shows that specific student groups in DE, classified as successful, non-successful and non-starting, can be distinguished by different characteristics. The investigated characteristics were measures related to demographics, health, life satisfaction, lifestyle, cognitive performance, study intention, living situation, computer abilities, work, learning restrictions (i.e., learning or psychological disorder), and medicine use. In terms of differences between successful and non-successful students, clear differences were observed in measures related to lifestyle, life satisfaction and perceived health related quality of life. From chapters 4, 5, and 6 could be concluded that none of the BLFs had a relation with learning performance. Chapter 7 shows that the BLFs do not predict EFs. For a more elaborate discussion of the specific findings see the respective chapters or the summary. The discussion below reviews these findings from a broader and more general perspective.

Discussion of this dissertation

The discussion of this dissertation focuses on three elements in order to explain the results found. First, there are two important concepts that require careful consideration: the operationalization of learning performance and the assumption that EFs predict learning. Second, no relations were observed between the BLFs and learning performance or performance on EFs. This could be because no true relations between the variables within the BLFs and performance on EFs or learning were present. However, it could also be that these relations could not be observed due to this dissertations' limitations (see *Strengths and Limitations*). Therefore, two possible underlying putative mechanisms that could be responsible for the hypothesized relations are also discussed: the possible interactions that BLFs can have resulting

from overlapping underlying physiological processes; and the putative epigenetic processes causing these underlying processes. Last, the execution of this four-year project led to new insights regarding the prediction of learning performance, which will be discussed.

Operationalization of learning performance

The operationalization of learning performance is a delicate issue as it is imperative to measure learning as good as possible. Learning performance was very difficult to operationalize in this research considering the non-fixed and modular form of education given at the Open University of the Netherlands. As indicated in the introduction of this dissertation, learning performance was chosen as the general umbrella term to indicate measures of performance in an educational setting. Operationalizing learning performance is highly important for the research conducted in this PhD project, as it is the main outcome measure.

Learning performance was measured as study progress in chapters 4, 5, and 6. Study progress is a continuous variable that provides more variation than a dichotomous measurement (i.e., success vs. non-success). Study progress was chosen as it was supposed to be the most reliable measure in this educational type. By using study progress as a variable, parametric methods could be used, increasing the likelihood of uncovering possible relations. Study progress was measured as the number of modules successfully completed over the subscription period (i.e., 14 months). One module is equal to 4.3 European Credits in the European Credit Transfer System. The nominal study load for one module is approximately 120 hours. However, operationalizing learning performance in this way brings with it an important consideration.

The modular system of the Open University of the Netherlands enables students to study one course, multiple courses, short or longer programs, or full academic degree programs. This offers a lot of freedom to the student and despite the fact that every participant in this research had the possibility to follow an equal number of courses and achieve the same number of credits, not every student had the same intention. As a result, not all students purchased an equal number of courses. To illustrate, there were students who only purchased a one-module course and managed to finish it within a few weeks or months. Intentions behind doing just one course were for example to formally certify a job-related competency, or to reduce the knowledge gap in order to enroll into a certain educational program at another institute. On the flip side were students who purchased more courses over the year, as they had a different study intention (e.g., they wanted to attain a bachelor degree). Students who only bought a one-module course and finished it, could, in essence, be considered highly successful students. They had successfully achieved what they intended to achieve. However, they are stuck at value 1 in the study progress measure (i.e., number of finished modules over 14 months), because of their intention to finish only one course. Students with the intention of achieving more courses could attain higher

values than 1 in the study progress measure, while possibly being slower in their study pace compared to the students who had the intention to just finish one course. What follows is that study progress is a way to reliably measure relative success between students, but its validity is confounded by the initial intention of students.

To explore and investigate this possible confounding, all analyses performed in chapters 4, 5, and 6 were re-executed over different selections of the data. The analyses from the first selection (see box 1) did not provide certainty about the confounding, therefore a second – more conservative – selection (see box 2) was made to fully investigate this possible confounding.

Box 1 | Additional analyses executed to investigate possible confounding in the outcome measure (selection 1)

In the survey conducted, participants were asked to indicate which goal they wanted to achieve when they started studying at the Open University of the Netherlands. They had 7 options to choose from, namely: (1) completing one or more courses; (2) attaining a (focus)degree program; (3) attaining a bachelor degree; (4) attaining a master degree; (5) attaining a pre-master program (i.e., to start a master degree program); (6) orientation; and (7) no specific goal. Based on their answer, the participants were classified into two groups: degree students and non-degree students, in order to separate the possible confounding students from the students that had the intention to study for a longer period. Thus, option 1, 6, and 7 were classified as non-degree students, the other options were classified as degree students. Appendix 4 shows the results from the analyses of this new selection. As indicated by the presented regression models, this new selection does not change the interpretation of the value of the predictors. The first conclusion, therefore, is that a more conservative selection, likely to prevent the confounding following study intention, does not lead to a different conclusion. This would mean that this confounding is not apparent.

A second conclusion, however, might go in a different direction. Closer inspection of the results presented in Appendix 4 indicates that the variables physical activity and fish consumption approach significance. It could be that this more conservative selection to eliminate the possible confounding is not conservative enough. Students indicating that they want to achieve a degree do not always seem to continue studying after their first exam attempt, despite indicating their clear goal. This is because these students have no study progress after 14 months (i.e., roughly 20% in the analyses of each BLF). Thus, in order to truly analyze the students who were studying over those 14 months subscription time, one needs to know whether they were still actively pursuing their goal over the entire 14 months. If an analysis could be executed with a selection on only those students who studied over the entire 14 months, it might lead to the emergence of significant predictor for the BLFs, if this confounding is applicable in the first place.

Box 2 | Additional analyses executed to investigate possible confounding in the outcome measure (selection 2)

In the ALOUD study, a second survey was conducted after 14 months (see chapter 2). In this survey the question was asked whether students were still studying at the moment of filling out the survey. Based on this question, an even more conservative selection can be made. Students who indicated that they were still studying after 14 months are very likely to be students who have studied over the entire 14 months. In any case, selecting only these students will ensure to tackle the intention problem described in this section as all students who finished studying before the survey were not included. Appendix 5 shows the analyses executed over this selection of the data. It can be concluded that the possible intention 'problem' is not a problem at all as the results indicate that no significant relations emerge. The variables physical activity and fish consumption that seemed to be approaching significance in Appendix 4, do not prove to be significant in this selection. Sleep duration on work days is significant in this selection (see *model B* in appendix 5). Comparing the covariate model with the model that included sleep duration on work days using a chi square comparison, shows no significant differences χ^2 (4, N = 472) = 8.322, p = .08. This means that, despite being a significant predictor, the model does not predict study progress better than the covariate model. Thus, the effect size of this variable in terms of explained variance is negligible.

Concluding, the confounded validity of the measure of learning performance operationalized as study progress seems not to be a real problem as indicated by these additional analyses. This ensures that the conclusions following from the analyses executed in chapters 4, 5, and 6 seem to be correct.

The assumption that executive functions predict learning

The many underlying physiological processes resulting from behavior within the variables of each BLF (see the respective chapters of this dissertation) are thought to affect the functioning of the brain. The resulting cognitive performance is consequently influenced, as shown by research regarding the BLFs physical activity (Barenberg, Berse, & Dutke, 2011), sleep (Durmer & Dinges, 2009) and nutrition (Dauncey, 2012). One would expect the cognitive benefits or disadvantages that arise from different behaviors on the BLFs to translate into learning. Specifically, EFs are assumed to be most important for learning (Diamond, 2013). The underlying assumption that performance on EFs translates into learning is 'evidenced' by research in traditional education, with children and adolescents showing performance on EFs to be a significant predictor for learning (e.g., Best, Miller, & Naglieri, 2011; Bull & Scerif, 2001; St Clair-Thompson & Gathercole, 2006; Van Dijk, De Groot, Savelberg, Van Acker,

& Kirschner, 2014). However, this provides no ultimate proof as no causal relation can be indicated by this observational research. Causal research regarding this assumed relation between EFs and learning is not apparent in traditional education. This link is very difficult to test causally as an experiment with the manipulation of EFs would ethically be highly questionable and even inappropriate. Therefore, researchers often use longitudinal research designs, though such research cannot absolutely establish a causal relationship. However, as it is generally accepted that cause precedes effect, longitudinal data provides enhanced causal inference compared with cross-sectional data and it is ideal when it is barely possible to use an intervention experiment.

First, this putative causal relation between EFs and learning is considered more thoroughly. A study using a specialized statistical technique investigated a possible causal relation using longitudinal data in traditional education (Willoughby, Kupersmidt, & Voegler-Lee, 2012). This technique – fixed effects analysis – does not rely on researchers to know all possible confounding variables, instead it uses longitudinal data to control for all confounding variation (i.e., known and unknown). Without using this technique, they found that the relation between EFs and academic achievement was similar to previous research, mentioned in the previous paragraph. However, when fixed effects analysis was applied, no significant relation remained (Willoughby et al., 2012). This means that when all confounding variation is controlled for, no relation remains between EFs and academic achievement in traditional education. This questions the causality of this relation and makes it debatable whether the assumption that EFs truly translate into learning is correct.

Chapters 4, 5 and 6 show that there is no relation between the BLFs and learning performance in the investigated DE population. These findings make the possible mediation that EFs may have on learning unimportant, as no relation between the BLFs and learning performance is present in the first place (Baron & Kenny, 1986). However, it could well be that a possible relation does not emerge, due to the limitations of the measurement of learning performance (which were mentioned in the previous section) or behavior on the BLFs (mentioned below in the section *Strength and limitations of this project*). Therefore, chapter 7 evaluated the variables within the BLFs being able to predict cognitive performance and specifically performance on the EFs. From this chapter it can be concluded that the variables within the BLFs do not predict EFs. Sedentary behavior only predicted processing speed. If a causal relation between EFs and learning would exist in adults, this means that the EFs measured are not involved as a mediator in the possible relation between BLFs and learning. The only EF measure not investigated was *inhibition*. From these findings it can be concluded that, for the EFs measured, there is no relation apparent between EFs and learning in adults as both the path between the independent variables (i.e., the BLFs) and the dependent variable (i.e., learning performance) and the path between the independent variables and the mediator (i.e., EFs) are not significant.

Concluding, this dissertation indicates that it is very unlikely that EFs mediate learning in adults. In addition, from the literature reviewed, it seems doubtful whether there is a causal relation between EFs and learning in traditional education as well.

Interactions between biological lifestyle factors

On the level of physiological processes resulting from behavior within the BLFs, interactions can occur that could lead to synergistic effects. Only recently, research is starting to focus on interactions between the BLFs. For example, the processes underlying the effects of omega-3 long-chain polyunsaturated fatty acids (n-3 LCPUFAs) and physical activity are partially overlapping. The levels of brain-derived neurotropic factor increase following the consumption of n-3 LCPUFAs and also following physical activity. This leads to a synergistic effect when combined, enhancing the effects both separate variables have (Van Praag, 2009).

Numerous interactions can exist considering the fact that many processes underlying the variables within each BLF are overlapping. These interactions are difficult to investigate but can have profound effects on the brain. Especially interactive synergistic effects can be optimally used when correctly combined. In such way, functioning of the brain and possibly learning can be easily brought to a higher level. However, the knowledge for this is lacking and the current investigation is too heterogeneous and observational to investigate these interactions. Surely, interactions could have been added in the analyses. However, as hypotheses were derived from theory and few insights regarding these interactions are available, this was not a viable approach to pursue.

Epigenetics

Epigenetic processes may be important mediating mechanisms in the effects that specific variables within the BLFs have. Epigenetics is the study of physiological variations which are not caused by changes in deoxyribonucleic acid (DNA), but are the result of changes in the transcription of the DNA. Epigenetic processes are vital for the development of cells (Reik, 2007). Changes in epigenetic profile can be long-lasting and can influence learning and memory (Gomez-Pinilla, Zhuang, Feng, Ying, & Fan, 2011). Changes in the transcription of the DNA are the result of various processes which are often influenced by environment (Tsankova, Renthal, Kumar, & Nestler, 2007). These changes not only seem to be important in developing neurons (Reik, 2007), but also in fully differentiated, mature neurons (Tsankova et al., 2007).

Some examples of how BLFs can influence epigenetics are presented. For physical activity it was shown that the increase in the neurotrophin brain-derived neurotropic factor following physical exercise is the result of epigenetic changes in the transcription of the DNA that codes for this neurotrophin (Gomez-Pinilla et al., 2011). For sleep, recent evidence shows that sleep deprivation leads to epigenetic modifications, which on its turn lead to inflammatory, immune and stress responses (Möller-Levet et al., 2013). For nutrition, research has found that a single serving of

broccoli led to epigenetic changes 3-6 hours after consumption (Dashwood & Ho, 2007). These examples show how epigenetic processes are mediating the effects that the BLFs have on the brain.

Research regarding epigenetic changes following behavioral changes related to these BLFs is in its infancy. Not only the interactions – mentioned in the previous section – caused by overlapping physiological effects are important. The causes of these processes are often also due to epigenetics changes, which can be triggered by behavior regarding the BLFs. In the end, this makes the physiology underlying the possible effects of these BLFs a complex story. Still, it is in important to realize the underlying processes as good as possible to provide a good theoretical background for all processes involved, not only on a behavioral level, but also on a physiological level.

Prediction models in distance education

Considering that this PhD project was funded directly by the Open University of the Netherlands, it is very useful to evaluate this research and to provide a clear direction for future research. The university would benefit most from research that provides the best prediction model for dropout and success. However, this was not the scope of this project when it was designed and executed. The research conducted within this dissertation originates from a biological perspective on learning. To formulate this more clearly, this dissertation focused on predicting learning performance (i.e., measured via study progress) from BLFs. In addition, the choices for the variables investigated were based on findings in traditional education as research in DE is scarce or even non-existent.

The findings in this dissertation provide insight on what factors may be important. Also, they provide insight on what factors may be unimportant. Chapter 3, which presents the characteristics of non-starting, non-successful and successful students, provides an interesting model for further research. This model – the model of persistence – classifies four categories of variables that could influence persistence in DE, namely (1) student characteristics, (2) student skills (factors affecting students prior to admission), (3) external factors and (4) internal factors (factors affecting students after admission) (Rovai, 2003). Furthermore, when looking at dropout (i.e., defined as non-starting), research also provides input on which characteristics may be important here (Lee & Choi, 2011). With this information taken together, it would be highly attractive to design a second version of ALOUD in which the set-up of the study is optimized, using the gained knowledge. Thus, the biological perspective would be abandoned and a more general perspective would be considered, in which all factors relevant to dropout and success would be included. Moreover, when executed at the Open University of the Netherlands, learning performance can be measured with more certainty as the educational model has changed from a modular non-fixed

[1] The Open University of the Netherlands recently switched to a new educational model (i.e., this was implemented in phases from September 2015 onwards). This means the education is no longer self-paced and has a fixed curriculum.

model to a fixed degree program[1]. Such a new version of the ALOUD project could be highly beneficial for the Open University of the Netherlands. The prediction models, resulting from this project, would provide more information for the Open University of the Netherlands and can assist the institution in tailor-made recommendations for students and tailor-made information for tutors/instructors guiding these students.

Strengths and limitations of this project

The research that was conducted for this dissertation has strengths and limitations. There are five major strengths of this research. First, this adult distance education population (i.e., students from the Open University of the Netherlands) has rarely been investigated in relation to learning performance. Hence, these new findings are an important starting point for the fields of educational science, physical activity, nutrition and sleep when it comes to individual differences regarding learning and cognition in normal adult age. Investigating these BLFs (i.e., physical activity, sleep, and nutrition) is a new and challenging approach, providing new insights in adults participating in DE; a unique population of students which is growing as people have to work and learn longer, which is why they often participate in formal continuing DE. Second, a phone call was made to make sure more people completed the research. The personal approach created more commitment, as reflected by the high increase of participants after the telephone call (i.e., response rates increased from around 15 to 30%). This approach also lowered the selection bias that could be present: It is likely that participants who fully participated were more motivated, not only for their participation in this research, but also for their own study. The personal phone call ensured that participants who were not so motivated also took part, reducing this potential bias. Third, the large data set provides a high power related to the findings and decreases the risk of contracting a type-1 error. Fourth, a large number of possible confounders was controlled for, eliminating possible spurious relations. Finally, the population investigated is a highly diverse population in terms of background characteristics, making it possible to generalize the results to a broad population.

Next to these strengths, the research conducted in this dissertation also has limitations. The design of the ALOUD study brings some limitations with it. The first and most important limitation is that the ALOUD study is an observational study which does not allow for causal inferences. Another limitation relates to the study population. As stated, the population investigated is a highly diverse population in terms of background characteristics, which is not only a strength but can also impede interpretation of the results. To specify, for example, the effects of specific behavior within the BLFs may be different over age or sex. The literature was taken into account regarding sex and age effects and other important covariates. However, possible interactive effects cannot be ruled out and are a risk in a heterogeneous population like the one used in this research. The limitations that follow have to do with the procedure of data collection. The data collected during the first measurement reflect the behavior of the participants around the start of their study. Learning performance

was calculated over the course of the initial subscription period (i.e., 14 months). Although it could be assumed that patterns regarding the BLFs are relatively stable over time, it is not possible to rule out changes in behavior on the BLFs over the course of these 14 months. Therefore, it could be possible that no results were found as behavior on these BLFs could have changed over that period of time. Furthermore, study progress is a fairly large-grained measure, but the best one available to measure learning performance, as discussed earlier (see O*perationalization of learning performance* section).

The limitations noted in this paragraph are applicable to all observational survey research in which self-report data is collected. Self-report introduces social desirability, which can distort true values on the measured variables. In addition, information regarding the memory one may have on certain questions regarding behavior can be missing or distorted. Next, the mood state of the participants at the moment of filling out the questionnaire can play a role. Last, time of participation could affect the data (e.g., morning/evening). However, these mood and time effects are likely to be smoothed out considering the large number of participants.

Another design issue has to do with the fact that participants were allowed to stop and continue later in the questionnaire. This was due to the long participation time (i.e., about 45 minutes for the survey and an additional 15 minutes for the cognitive tests) and this option was thought to increase the response rate as it provided the participants with more freedom. This delayed participation over time could provide distortions in the data following from the earlier mentioned mood and time effects. However, as stated before, these distortions are likely to be smoothed out resulting from the number of participants.

Last, participation in this research was limited as the survey and cognitive tests needed to be executed on a desktop computer or laptop; compatibility on mobile devices was not guaranteed. In addition, two out of the three cognitive tests required a separate regular pointing device (i.e., the regular 'mouse'), which was a limitation for a number of participants: About 20% of all participants who completed the survey did not finish the cognitive tests. The cognitive tests that were executed right after the questionnaire carried an instruction asking the participant to execute these tasks in a quiet place without any distraction. Despite this instruction, the environment in which the tests were made, were uncontrollable and could possibly have influenced the results.

Implications for future research

The question remains whether these BLFs are truly not predictive for learning, or, that limitations applicable to this investigation are preventing eventual relations to emerge. None of the variables measured within the BLFs were significantly associated with learning performance. Despite this, it was expected that some of these variables were in fact associated with learning performance. These were the variables physical activity, sedentary behavior, sleep duration and sleep quality (see chapters 4 and 5).

It would be desirable to design a stronger observational study with a longitudinal design into these variables with regard to learning performance. For physical activity and sedentary behavior, such a study would use objective (e.g., using accelerometry) and subjective measurement (e.g., using experience sampling method). Research namely shows that there is a significant difference between objective and subjective measurements (Syväoja et al., 2013). In addition, regarding sedentary behavior, subjective measurement is imperative, next to objective measurement, as it is important to record which type of sedentary behavior activity is happening (Rhodes, Mark, & Temmel, 2012). For sleep related measures, such a study would use objective (e.g., wrist actigraphy) or subjective measurement (e.g., sleep log diaries) to investigate the behavior more thoroughly. Both measurements can be satisfactory, as sleep duration and sleep quality can be reliably and validly measured by both methods (Ancoli-Israel et al., 2003). For both studies, it would be important to validly measure learning performance. Therefore, a fixed-paced curriculum would be most suitable as all students would have the same pace and order of courses.

It is thus uncertain whether a true relationship exists between BLFs and learning. From the research executed in this dissertation is concluded that – bearing in mind the limitations – BLFs are not related to learning. If true, this means that generalizing the results found in traditional education among children and adolescents seems not to be a good basis for research in adults participating in DE. These two populations of students are probably too different to generalize findings from one population to another.

Regarding the prediction of cognitive performance, none of the biological variables were predictive for executive functioning. Following the discussion (see the section *The assumption that executive functions predict learning*), it seems that EFs are not predictive for learning performance in adults participating in DE. However, considering the limitations of the learning performance measure it would be highly interesting to investigate the relation between EFs and learning performance more closely. Additionally, it would be advised to include a measure for every EF, since *inhibition* was missing in this investigation. In the literature, there are three measures considered to be involved in EFs: shifting, updating and inhibition (Miyake et al., 2000). Students are often online when studying and other online activities may be more appealing (e.g., being active on a social network or reading news), which could distract them from their studies. Especially inhibition is an important EF that inhibits these distractions. Considering that the cognitive tests were collected digitally, it was at the time designing the study practically not possible to incorporate an inhibition task as well.

Besides emphasizing the biological perspective, another perspective can be taken, which is the usefulness of future research for DE institutions. The perspective comes from chapter 3 and is discussed in the section *Prediction models in distance education*. This section focuses on the development of a prediction model for dropout and success in DE, providing valuable input for DE institutions from which tailored advice can be extracted and given to students and teachers. It would be valuable for

a distance university to focus more on the general prediction of learning performance from measures that are deemed influential from a perspective as broad as possible. Distance universities can then optimize their efficiency and their investment. This could also add to the personal efficiency of students as advice could be provided based on the prediction.

Last, advice regarding international research is difficult as educational models are often different as are the resulting measurements of learning performance. Regarding chapter 3 – the study into the characteristics of different types of students – it is first of all important to make sure there is an international comparable standard for success, persistence and dropout in DE (Grau-Valldosera & Minguillón, 2014). As indicated by these authors, definitions are incongruent imposing strong limitations on the comparison of the literature. By using international comparable standards, research findings itself will be comparable and more valuable.

Implications for educational practice

The findings regarding the characteristics presented in chapter 3 provide the institution (i.e., the Open University of the Netherlands) with more insight into factors influencing whether students actually start their study and when they do, whether they are successful or not. This information can be used as a starting point for a more comprehensive study into the prediction of students' behavior regarding actual participation in the program and success. This is mentioned earlier in this discussion (the sections *Prediction models in distance education* and *Implications for future research*). Leaving the biological perspective and aiming at predicting success and dropout (i.e., defined as non-starting) as accurately as possible using all known predictors from a broad general perspective would be very desirable for the Open University of the Netherlands, but also other DE institutions in general.

The prediction of learning performance from a biological perspective – investigated in chapters 4, 5 and 6 – provides the institution with information regarding the personal lifestyle of students. The investigated BLFs physical activity, sleep and nutrition do not seem to have any association with learning performance. This indicates that regarding learning performance the BLFs do not seem to be important in DE. However, important to note here is that the limitations mentioned earlier need to be taken into account. Nevertheless, it seems to be that investigating these BLFs in DE is not a viable approach and efforts could be invested elsewhere.

Concluding, this dissertation provides a starting point for educational practice with regard to a biological perspective, in this specific instance the educational practice of open adult distance education on a higher education level using a modular system. This dissertation shows that BLFs do not seem to provide an interesting path to follow when it comes to the prediction of learning performance. It does, however, provide opportunities and insight for continuing research regarding the prediction of learning performance from a more general perspective. Basically, it is advised to develop a new study, in the new educational model of the Open University of the Netherlands, aiming to predict success and dropout.

APPENDICES

Appendix 1

Following the section *Characteristics* in the *Methods*, this appendix contains more information on the separate variables, clustered following Rovai's model (2003) and a clustering to types.

Characteristics of students prior to admission
The characteristics prior to admission are clustered into: Demographics; health, life satisfaction and lifestyle; cognitive performance; study intention; and living situation.

Demographics

- age, as memory performance declines with increasing age (Grady & Craik, 2000), possibly hampering learning efficiency;
- age group, as the population of DE students is highly diverse in terms of age and previous research analyzed age in groups (Park & Choi, 2009), age is also investigated over certain age groups to investigate possible differences and map the heterogeneous group better;
- sex, as there are profound sex differences in intelligence (e.g., on the domains of memory, reasoning and science) which could influence learning. There are intellectual domains where males excel females (e.g., spatial reasoning) and vice versa (e.g., verbal fluency) (Halpern, 1997);
- nationality, as non-Dutch nationals could experience difficulties since most courses are in the Dutch language;
- native language, as non-Dutch speakers could have more difficulties with the language;
- level of previous education (ordinal variable with eight levels following de Bie, (1987), as previous level of education has been found to be a significant predictor of academic success for students (Bernt & Bugbee, 1993);
- level of previous education of the partner (if applicable) (de Bie, 1987), as this highly correlates with the level of education of the participant under investigation (M. Kalmijn, 1998; Komter, Keizer, & Dykstra, 2012).

Health, life satisfaction and lifestyle

- body mass index (computed from weight and height), as it is negatively associated with learning performance (Crosnoe & Muller, 2004);
- alcohol consumption (in standard glasses per week), as it has been found to influence study progress (Singleton & Wolfson, 2009);
- smoking (whether someone smokes or not), as the use of tobacco has negative implications on cognition (Caspers, Arndt, Yucuis, McKirgan, & Spinks, 2010; Fried, Watkinson, & Gray, 2006; S. Kalmijn, Van Boxtel, Verschuren, Jolles, & Launer, 2002), which could translate into impaired learning;

- life satisfaction, investigated using the satisfaction with life questionnaire (Diener, Emmons, Larsen, & Griffin, 1985), as more satisfaction is synergistic with better learning (Seligman, Ernst, Gillham, Reivich, & Linkins, 2009);
- health related quality of life, investigated using the RAND-36, a questionnaire providing 9 scale scores on: physical functioning; social functioning; physical role limit; emotional role limit; mental health; vitality; pain; general health perception; and health change (i.e., over the last year) (Hays & Morales, 2001).

Cognitive performance

- performance on the substitution test (i.e., resembles the symbol digit modalities test of Smith, 1991), resulting in a measure of information processing speed, measured as the number of items correctly substituted in 90 seconds;
- performance on the N-back task (Lezak, Howieson, & Loring, 2004), resulting in a measure for working memory and the executive function updating, measured via the number of correctly remembered items;
- performance on the Trail Making Test (Army Individual Test Battery, 1944), resulting in a measure for the executive function shifting, measured via the B-A part.

Study intention

- expected average number of study hours per week to be invested (as reported by the students), as more time invested is likely to lead to better results (Bernt & Bugbee, 1993);
- study goal, general goal for studying (i.e., one or more courses, short study program, bachelor degree, master degree, premaster, orientation, no specific goal), the main intention of students to start studying (e.g., orientation or an entire bachelor degree), as this indicates the intention to succeed;
- specific study goal (expected number of completed modules after 6 months), provides a clear estimation of the expectation and hence the intention of the study progress to be made;
- study motive (personal or professional), as intrinsic motivation is a better motivator for learning than external triggers (Ryan & Deci, 2000).

Living situation

- living situation describes the living situation of the participant (e.g., living alone, living with partner, living with partner and children, living with parents, etc.). As social support gained from immediate surroundings is a key element in successful learning (Crean, 2004), living situation is an important variable to take into account;
- number of children living at home, as this could possibly provide distractions from learning.

Skills of students prior to admission

- computer abilities (measured via a self-developed questionnaire mapping attitude, confidence, and skills towards the use of a computer), as students use an electronic learning environment, which could be a disadvantage when being not very 'computer-adjusted'.

External factors affecting students after admission

The external factors affecting students after admission are clustered into: Work related measures; learning restrictions (learning or psychological disorder); and medication use.

Work related measures

- type of work contract, whether someone works part time, full time or not at all. One would expect that students with more job commitments would perform less. However, it has been found that workers with less than 20 work hours per week perform worse than their counterparts working more (Taplin & Jegede, 2001), making it important to review this characteristic;
- regularity of work times, as it has been shown that low achievers are more likely to have irregular work times (Taplin & Jegede, 2001);
- number of working hours per week, as common sense and literature (Eppler & Harju, 1997) suggests that more working hours lead to less study progress, as less study time is remaining. However, as indicated above, this is not necessarily the case (Taplin & Jegede, 2001).

Learning restrictions

- learning restriction, as certain restrictions (i.e., officially recognized psychological problems or learning disorders) can impose problems regarding the learning process;
- medication side effects, as the use of certain medication can have implications on the learning capacity. Each individually reported medicament was manually scored by its possible side effects.

Appendix 2

Characteristics of students prior to admission

Demographics

TABLE 2. Descriptives and results of the analyses for the interval variables

Variable	Successful	Non-successful	Non-starters	*P*-value
Age (years)	36.11 (11.26)[b#]	34.80 (10.47)[b#]	39.07 (11.01)	<.001

Number represent mean and standard deviation in brackets. N=918 for the successful group, N=246 for the non successful group and N=827 for the non starters group. P value is based on the F statistic of the ANOVA. Post-hoc differences are depicted with Bonferroni corrections in superscript letters: b=significantly different from non starters, the hashtags indicate the level of significance: #<.001.

TABLE 3. Descriptives and results of the analyses for the categorical variables

Variable	Level	Successful	Non-successful	Non-starters	*P*-value	Corr.
Sex	Men Women	340 (37.0) 578 (63.0)	90 (36.6) 156 (63.4)	334 (40.4) 493 (59.6)	.295	N/A
Nationality	Not Dutch Dutch	100 (10.9) 818 (89.1)	21 (8.5) 225 (91.5)	115 (13.9) 712 (86.1)	.034	.058
Native language	Not Dutch Dutch	39 (4.2) 879 (95.8)	25 (10.2) 221 (89.8)	50 (6.0) 777 (94.0)	.002	.080
Educational level*	1 2 3 4 5 6 7 8	5 (0.5) 4 (0.4) 56 (6.1) 59 (6.4) 97 (10.6) 357 (39.0) 261 (28.5) 77 (8.4)	5 (2.1) 1 (0.4) 20 (8.2) 34 (14.0) 41 (16.9) 72 (29.6) 52 (21.4) 18 (7.4)	8 (1.0) 4 (0.5) 47 (5.7) 110 (13.3) 93 (11.2) 300 (36.3) 173 (20.9) 92 (11.1)	<.001	.121
Educational level of the partner*	1 2 3 4 5 6 7 8	3 (0.5) 11 (1.9) 24 (4.1) 114 (19.6) 16 (2.7) 182 (31.2) 172 (29.5) 61 (10.5)	1 (0.8) 5 (3.8) 8 (6.0) 34 (25.6) 7 (5.3) 41 (30.8) 23 (17.3) 14 (10.5)	3 (0.6) 11 (2.1) 33 (6.4) 106 (20.6) 28 (5.4) 150 (29.2) 118 (23.0) 65 (12.6)	.078	N/A
Age group	18–24 25–29 30–39 40–49 50–59 60–64 65+	161 (17.5) 176 (19.2) 260 (28.3) 19 (21.6) 94 (10.2) 19 (2.1) 10 (1.1)	44 (17.9) 54 (22.0) 77 (31.3) 45 (18.3) 21 (8.5) 3 (1.2) 2 (0.8)	73 (8.8) 135 (16.3) 234 (28.3) 239 (28.9) 118 (14.3) 16 (1.9) 12 (1.5)	<.001	.118

Number represents count and column percentage in brackets. The correlation represents Cramer's V correlation with its corresponding *P*-value. N/A means not applicable. * The coding of the variable *Educational level* represent the following levels: 1=Lower general education; 2=Lower vocational education; 3=Average general education; 4=Average vocational education; 5=Secondary general education; 6=Higher vocational education; 7=Higher general/scientific education; 8=Post-higher/Post-university education. The variable *Educational level* does not contain all participants because a small number of participants filled in the option 'other', but did not respond in the subsequent answer box. The variable *Educational level of the partner* does not contain all participants as only participants who reported to have a partner, had to fill in this information.

Health, life satisfaction and lifestyle

TABLE 4. Descriptives and results of the analyses for the interval variables

Variable	Successful	Non-successful	Non-starters	*P*-value
Body mass index (kg/m^2)	23.53 (3.77)$^{a\#,b\#}$	24.81 (4.67)	24.67 (4.28)	<.001
Alcohol consumption (standard glasses per week)	3.60 (5.53)	3.04 (5.13)	3.72 (6.43)	.287
Life satisfaction (scale score)	25.57 (5.33)$^{a\#,b\#}$	23.85 (5.94)	24.60 (5.66)	<.001
R–Physical functioning (scale score)	94.57 (11.29)$^{b\#}$	93.27 (12.89)	92.50 (13.21)	.002
R–Social functioning (scale score)	88.09 (18.37)$^{a\#,b\#}$	82.27 (20.67)	83.30 (22.28)	<.001
R–Physical role limit (scale score)	88.13 (27.27)$^{a**,b\#}$	80.89 (34.64)	82.16 (33.30)	<.001
R–Emotional role limit (scale score)	85.66 (30.45)$^{a\#,b\#}$	74.66 (38.26)	76.46 (37.82)	<.001
R–Mental health (scale score)	76.01 (13.84)^{a*}	73.19 (16.91)	74.47 (15.42)	.012
R–Vitality (scale score)	66.77 (15.72)$^{b\#}$	64.15 (17.38)	63.79 (17.36)	<.001
R–Pain (scale score)	87.08 (17.04)^{a*,b**}	83.29 (21.54)	84.20 (20.60)	.001
R–General health perception (scale score)	72.11 (17.79)^{b*}	70.53 (17.78)	69.82 (17.84)	.025
R–Health change (scale score)	57.05 (19.08)	59.15 (22.54)	56.29 (21.23)	.156

Number represent mean and standard deviation in brackets. N=918 for the successful group, N=246 for the non-successful group and N=827 for the non-starters group. 'R' means RAND 36. *P*-value is based on the F statistic of the ANOVA. Post-hoc differences are depicted with Bonferroni corrections in superscript letters: a=significantly different from non-successful, b=significantly different from non-starters, the asterisks/hashtags indicate the level of significance: *<.05, **<.01, #<.001.

TABLE 5. Descriptives and results of the analyses for the categorical variables

Variable	Level	Successful	Non-successful	Non-starters	P-value	Corr.
Smoking	Non-smokers Smoker	765 (83.3) 153 (16.7)	189 (76.8) 57 (23.2)	633 (76.5) 194 (23.5)	<.001	.083

Number represent count and column percentage in brackets. The correlation represents Cramer's V correlation with its corresponding *P*-value.

Cognitive performance

TABLE 6. Descriptives and results of the analyses for the interval variables

Variable	Successful	Non-successful	Non-starters	*P*-value
Processing speed (items finished)	50.34 (8.45)[754;b#]	50.01 (8.77)[187]	48.63 (8.26)[608]	<.001
Shifting (B-A part, in seconds)	20.39 (16.62)[737]	22.94 (22.94)[180]	22.43 (15.69)[600]	.047
Updating (correctly answered items)	55.73 (5.44)[737;b*]	55.15 (6.13)[178]	54.90 (6.19)[594]	.031

Number represent mean and standard deviation in brackets. The superscript number represents the N. *P*-value is based on the F statistic of the ANOVA. Post-hoc differences are depicted with Bonferroni corrections in superscript letters: b=significantly different from non-starters, the asterisks/hashtags indicate the level of significance: *<.05, #<.001.

Study intention

TABLE 7. Descriptives and results of the analyses for the interval variables

Variable	Successful	Non-successful	Non-starters	*P*-value
Expected study hours (per week)	13.13 (7.40)[a*,b#]	14.61 (8.20)[b#]	10.49 (6.66)	<.001
Specific study goal (modules expected to finish)	3.31 (2.18)[631;b#]	3.30 (2.00)[158;b#]	2.49 (1.76)[447]	<.001

Number represent mean and standard deviation in brackets. The superscript number represents the N. *P*-value is based on the F statistic of the ANOVA. Post-hoc differences are depicted with Bonferroni corrections in superscript letters: a=significantly different from non-successful, b=significantly different from non-starters, the asterisks/hashtags indicate the level of significance: *<.05, #<.001.

TABLE 8. Descriptives and results of the analyses for the categorical variables

Variable	Level	Successful	Non-successful	Non-starters	*P*-value	Corr.
Study motive	Personal	527 (57.5)	135 (54.9)	493 (59.7)	.359	N/A
	Professional	390 (42.5)	111 (45.1)	333 (40.3)		
Study goal	One or more courses	205 (22.3)	47 (19.1)	197 (23.8)	<.001	.109
	Short study program	51 (5.6)	14 (5.7)	73 (8.8)		
	Bachelor degree	320 (34.9)	110 (44.7)	245 (29.6)		
	Master degree	221 (24.1)	50 (20.3)	178 (21.5)		
	Premaster	66 (7.2)	12 (4.9)	42 (5.1)		
	Orientation	40 (4.4)	11 (4.5)	59 (7.1)		
	No specific goal	15 (1.6)	2 (0.8)	33 (4.0)		

Number represent count and column percentage in brackets. The correlation represents Cramer's V correlation with its corresponding *P*-value. N/A means not applicable. In the variable Study motive there is 1 missing value in both the successful and non-starters group.

Living situation

TABLE 9. Descriptives and results of the analyses for the categorical variables

Variable	Level	Successful	Non-successful	Non-starters	*P*-value	Corr.
Living situation	With (grand)parents Alone With children With partner With partner and children	103 (11.6) 174 (19.6) 27 (3.0) 280 (31.5) 305 (34.3)	36 (15.1) 59 (24.7) 11 (4.6) 54 (22.6) 79 (33.1)	74 (9.1) 170 (21.0) 50 (6.2) 215 (26.5) 301 (37.2)	<.001	.082
Number of children that live at home	1 2 3 4 5 or more	85 (25.6) 168 (50.6) 63 (19.0) 14 (4.2) 2 (0.6)	32 (35.6) 39 (43.3) 16 (17.8) 2 (2.2) 1 (1.1)	121 (34.5) 162 (46.2) 60 (17.1) 7 (2.0) 1 (0.3)	.224	N/A

Number represent count and column percentage in brackets. The correlation represents Cramer's V correlation with its corresponding *P*-value. N/A means not applicable. The variable *Living situation* does not contain all participants because a small number of participants filled in the option 'other', but did not respond in the subsequent answer box. The variable *Number of children that live at home* does not contain all participants as only participants who reported to have children living at home, had to fill in this information.

Skills of students prior to admission

TABLE 10. Descriptives and results of the analyses for the interval variables

Variable	Successful	Non-successful	Non-starters	*P*-value
Computer abilities (scale score)	42.57 (5.82)	43.37 (5.86)	42.93 (6.19)	.133

Number represent mean and standard deviation in brackets. N=918 for the successful group, N=246 for the non-successful group and N=827 for the non-starters group. *P*-value is based on the F statistic of the ANOVA. There were no post-hoc differences.

Characteristics of students prior to admission

Work related measures

TABLE 11. Descriptives and results of the analyses for the interval variables

Variable	Successful	Non-successful	Non-starters	*P*-value
Work hours (per week)	25.99 (15.58)^{b**}	24.74 (17.48)^{b**}	28.41 (15.91)	<.001

Number represent mean and standard deviation in brackets. N=918 for the successful group, N=246 for the non-successful group and N=827 for the non-starters group. P value is based on the F-statistic of the ANOVA. Post-hoc differences are depicted with Bonferroni corrections in superscript letters: b=significantly different from non-starters, the asterisks indicate the level of significance: **<.01.

TABLE 12. Descriptives and results of the analyses for the categorical variables

Variable	Level	Successful	Non-successful	Non-starters	*P*-value	Corr.
Work schedule	Regular Not regular	561 (72.3) 215 (27.7)	125 (65.1) 67 (34.9)	497 (68.5) 229 (31.5)	.085	N/A
Work type	Full time Part time Not working	424 (46.2) 352 (38.3) 142 (15.5)	107 (43.5) 85 (34.6) 54 (22.0)	451 (54.5) 275 (33.3) 101 (12.2)	<.001	.077

Number represent count and column percentage in brackets. The correlation represents Cramer's V correlation with its corresponding *P*-value. N/A means not applicable. The variable Work schedule does not contain all participants because of tailoring.

Learning restrictions

TABLE 13. Descriptives and results of the analyses for the categorical variables

Variable	Level	Successful	Non-successful	Non-starters	*P*-value	Corr.
Learning restriction	No	877 (95.5)	221 (89.8)	762 (92.1)	<.001	.084
	Yes	41 (4.5)	25 (10.2)	65 (7.9)		
Medication side effects	Unknown	26 (12.2)	7 (11.7)	25 (13.0)	.006	.162
	Non-interfering (int.)	112 (52.6)	20 (33.3)	73 (37.8)		
	Possible cognitively int.	28 (13.1)	11 (18.3)	31 (16.1)		
	Definitely cognitively int.	14 (6.6)	6 (10.0)	29 (15.0)		
	Mentally int.	24 (11.3)	7 (11.7)	25 (13.0)		
	Cognitively + mentally int.	9 (4.2)	9 (15.0)	10 (5.2)		

Number represent count and column percentage in brackets. The correlation represents Cramer's V correlation with its corresponding *P*-value. The variable *Medication side effects* does not contain all participants as only participants who reported the use of medication had to fill in this information.

Appendix 3

Characteristics of students prior to admission

Variable	Mean	SD	Range	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.
1. Total work hours per week	30.94	12.11	0-84	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2. Expected study hours per week	12.30	6.48	1-40	-.198**	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
3. Age in years	36.15	10.45	18-68	-.003	-.131	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
4. Body mass index in kg/m2	24.03	3.92	17-50	.066*	.028	.213**	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5. Computer abilities (percentage)	42.72	5.81	16-52	.170**	.071*	-.106*	.100*	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
6. Expected finished modules (6 months)	2.26	2.29	0-14	-.035	.402**	-.102*	.009	.150**	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-
7. Alcohol consumption per week	3.11	4.61	0-28	.062	-.027	.158**	.006	.040	-.002	1	-	-	-	-	-	-	-	-	-	-	-	-	-
8. Life satisfaction (percentage)	25.48	5.43	5-35	.121**	-.146**	.123**	-.067*	-.002	-.024	.020	1	-	-	-	-	-	-	-	-	-	-	-	-
9. Chronotype (MSFsc)	3:49	0:55	1:15-7:00	.047	.115**	-.275**	-.060	.060	.069*	.150**	-.178**	1	-	-	-	-	-	-	-	-	-	-	-
10. Sleep duration (work)	7:56	0:56	5:00-11:00	-.258**	.004	-.139**	-.076*	-.036	-.039	-.070*	-.033	.060	1	-	-	-	-	-	-	-	-	-	-
11. Sleep duration (free)	8:30	1:07	5:00-12:00	-.163**	-.008	-.261**	-.121**	-.076*	-.005	-.103*	.008	-.008	.431**	1	-	-	-	-	-	-	-	-	-
12. Sleep duration polynomial (work)	0.88	1.46	0.01-9.44	-.096*	.168**	-.076*	.026	.017	.020	-.005	-.110**	.162**	.102*	.078*	1	-	-	-	-	-	-	-	-
13. Sleep duration polynomial (free)	1.23	1.89	0.00-12.29	-.020	.040	-.090*	-.010	.028	.040	.007	-.104*	.165**	-.030	-.003	.267**	1	-	-	-	-	-	-	-
14. Sleep quality	-	-	-	.021	.011	.081*	-.074*	.064	.045	-.002	.189**	-.044	.028	-.024	-.033	-.032	1	-	-	-	-	-	-
15. Sex (0=male)	-	-	-	-.239**	-.097*	-.063	-.155**	-.233**	-.064	-.163**	.051	-.134**	.198**	.198**	-.083*	.013	-.031	1	-	-	-	-	-
16. Nationality (1=Dutch)	-	-	-	-.077*	-.051	.049	.018	-.024	-.031	.010	.066*	-.009	.080*	.021	-.016	-.022	.007	.021	1	-	-	-	-
17. Native language (1=Dutch)	-	-	-	-.002	-.036	.027	-.036	-.032	.024	.096*	-.008	-.041	.091*	.042	-.058	.034	-.041	-.030	.127**	1	-	-	-
18. Educational level dummy for high (1=high)	-	-	-	-.006	.071*	-.103*	.055	.032	.054	.031	.012	.066*	.056	.080*	.022	.002	.023	.024	.193**	.064	1	-	-
19. Educational level dummy for university (1=university)	-	-	-	.036	-.170**	.152**	-.066*	-.030	-.073*	.027	.128**	-.068*	-.023	-.077*	-.087*	-.044	.052	.028	-.113**	-.047	-.727**	1	-
20. Study motive (0=personal, 1=professional)	-	-	-	-.029	.051	-.063	.000	-.010	.073*	-.041	-.051	.000	.014	.020	-.012	.009	.005	.097*	-.049	.022	-.144**	.156**	1

Appendix 4

Additional analyses conducted over only degree students

TABLE 1. Generalized linear regression (negative binomial) for the BLF physical activity

Predictor variable	β (standardized)	Significance (p-value)
Model A (χ^2=51.389, df=5, p<0.001)		
Expected study hours	.108	.005
Expected number of completed modules after 6 months	.103	.002
Alcohol consumption per week	.110	.002
Life satisfaction	.078	.023
Native language[1]	.585	<.001
Model B (χ^2=56.165, df=7, p<0.001)		
Expected study hours	.106	.006
Expected number of completed modules after 6 months	.101	.002
Alcohol consumption per week	.106	.003
Life satisfaction	.086	.013
Native language[1]	.584	<.001
Physical activity intensity score	-.061	.080
Sedentary behavior in minutes per week	.038	.270

[1] *This dichotomous variable is not standardized; N=715.*

TABLE 2. Generalized linear regression (negative binomial) for the BLF sleep

Predictor variable	β (standardized)	Significance (p-value)
Model A (χ^2=58.670, df=6, p<0.001)		
Expected study hours	.107	.005
Body mass index (kg/m^2)	-.129	<.001
Expected number of completed modules after 6 months	.109	.002
Alcohol consumption per week	.067	.048
Life satisfaction	.107	.003
Native language[1]	.516	.003
Model B (χ^2=61.864, df=10, p<0.001)		
Expected study hours	.105	.006
Body mass index (kg/m^2)	-.124	<.001
Expected number of completed modules after 6 months	.109	.002
Alcohol consumption per week	.070	.042
Life satisfaction	.107	.004
Native language[1]	.496	.004
Sleep quality[1]	.018	.803
Chronotype	-.006	.865
Sleep duration (work days)	.059	.131
Sleep duration (free days)	.008	.839
Model C (χ^2=62.253, df=12, p<0.001)		
Expected study hours	.110	.005
Body mass index (kg/m^2)	-.124	<.001
Expected number of completed modules after 6 months	.107	.002
Alcohol consumption per week	.070	.041
Life satisfaction	.107	.004
Native language[1]	.492	.004
Sleep quality[1]	.016	.825
Chronotype	-.005	.891
Sleep duration (work days)	.062	.116
Sleep duration (free days)	.009	.810
Sleep duration polynomial (work days)	-.022	.533
Sleep duration polynomial (free days)	.005	.887

[1] *This dichotomous variables were not standardized as this does not enhance interpretation; N=664.*

TABLE 3. Generalized linear regression (negative binomial) for the BLF nutrition

Predictor variable	β (standardized)	Significance (p-value)
Model A (χ^2=58.194, df=5, p<0.001)		
Expected study hours	.100	.005
Expected number of completed modules after 6 months	.114	<.001
Alcohol consumption per week	.089	.004
Life satisfaction	.080	.015
Native language[1]	.642	<.001
Model B (χ^2=62.525, df=8, p<0.001)		
Expected study hours	.106	.003
Expected number of completed modules after 6 months	.110	<.001
Alcohol consumption per week	.094	.003
Life satisfaction	.083	.012
Native language[1]	.619	<.001
Caffeine consumption	.031	.355
Fish consumption	-.059	.091
Breakfast consumption	.030	.384

[1] *This dichotomous variable is not standardized; N=837.*

Appendix 5

Additional analyses conducted over students still studying at the moment of the second survey

TABLE 1. Generalized linear regression (negative binomial) for the BLF physical activity

Predictor variable	β (standardized)	Significance (p-value)
Model A (χ^2=57.007, df=6, p<0.001)		
Expected study hours	.121	.001
Age	-.087	.015
Expected number of completed modules after 6 months	.086	.011
Alcohol consumption per week	.095	.003
Life satisfaction	.086	.015
Native language[1]	.628	.003
Model B (χ^2=61.039, df=8, p<0.001)		
Expected study hours	.122	.001
Age	-.077	.033
Expected number of completed modules after 6 months	.083	.015
Alcohol consumption per week	.092	.004
Life satisfaction	.091	.010
Native language[1]	.628	.003
Physical activity intensity score	-.054	.118
Sedentary behavior in minutes per week	.037	.290

[1] *This dichotomous variable is not standardized; N=507.*

TABLE 2. Generalized linear regression (negative binomial) for the BLF sleep

Predictor variable	β (standardized)	Significance (p-value)
Model A (χ^2=45.774, df=5, p<0.001)		
Expected study hours	.140	<.001
Body mass index (kg/m^2)	-.073	.045
Expected number of completed modules after 6 months	.091	.011
Alcohol consumption per week	.080	.016
Life satisfaction	.092	.012
Model B (χ^2=54.096, df=9, p<0.001)		
Expected study hours	.139	<.001
Body mass index (kg/m^2)	-.071	.052
Expected number of completed modules after 6 months	.091	.011
Alcohol consumption per week	.090	.008
Life satisfaction	.098	.009
Sleep quality[1]	-.024	.739
Chronotype	-.017	.655
Sleep duration (work days)	.096	.014
Sleep duration (free days)	.010	.803
Model C (χ^2=54.290, df=11, p<0.001)		
Expected study hours	.141	<.001
Body mass index (kg/m^2)	-.071	.051
Expected number of completed modules after 6 months	.090	.013
Alcohol consumption per week	.090	.008
Life satisfaction	.098	.009
Sleep quality[1]	-.025	.730
Chronotype	-.014	.716
Sleep duration (work days)	.099	.013
Sleep duration (free days)	.011	.785
Sleep duration polynomial (work days)	-.015	.682
Sleep duration polynomial (free days)	-.001	.975

[1] *This dichotomous variables were not standardized as this does not enhance interpretation; N=472.*

TABLE 3. Generalized linear regression (negative binomial) for the BLF nutrition

Predictor variable	β (standardized)	Significance (p-value)
Model A (χ^2=48.784, df=4, p<0.001)		
Expected study hours	.118	<.001
Expected number of completed modules after 6 months	.104	.002
Alcohol consumption per week	.088	.004
Native language[1]	.552	.004
Model B (χ^2=50.402, df=7, p<0.001)		
Expected study hours	.114	<.001
Expected number of completed modules after 6 months	.107	.001
Alcohol consumption per week	.090	.004
Native language[1]	.558	.004
Caffeine consumption	-.029	.379
Fish consumption	.018	.590
Breakfast consumption	.025	.453

[1] *This dichotomous variable is not standardized; N=589.*

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SUMMARY

Environmental factors play an important role in the development of cognitive and learning capacities. Certain aspects of physical activity (e.g., active vs. passive behavior: Fedewa & Ahn, 2011; Tremblay et al., 2011), sleep (e.g., sleep duration and quality: Dewald, Meijer, Oort, Kerkhof, & Bögels, 2010) and nutrition (e.g., breakfast and poly-unsaturated fatty acids: Frensham, Bryan, & Parletta, 2012) are predictive for learning performance in children and adolescents in traditional education. Such factors are called biological lifestyle factors (BLFs). There is no reason that these BLFs should not also influence learning performance in other educational settings. The goal of this dissertation is to investigate the relation between variables within the domain of these BLFs on the one hand and learning performance and cognitive performance on the other in a distance education (DE) setting. This investigation was executed within the Adult Learning Open University Determinants (ALOUD) study.

Theoretical background

Chapter 1 emphasizes the importance of the research population, which is the DE student. The terms DE, learning performance and cognition, which are relevant to this research are explained. Furthermore, it is explained why this research is executed in DE specifically and the BLFs are extensively discussed. The putative mechanisms held responsible for the found relations between de BLFs and learning performance and cognition are discussed. The aim of this dissertation was first to explore the characteristics of different student groups (i.e., successful, non-successful, and non-starting). The second aim was to examine whether BLFs predicted learning performance. Third, it aimed to investigated whether the BLFs predicted cognitive performance, as it can be a predictor for learning in traditional education. Last, the aim was to determine whether a possible relation between the BLFs and learning performance was mediated by executive functions (EFs).

Set-up of the ALOUD study

Chapter 2 describes the ALOUD study. The association between biological and psychological factors and learning performance has been well established for children and adolescents in traditional education. Evidence for these associations in adult DE is lacking however. The ALOUD study is the first large-scale investigation of psychological and biological determinants of learning performance in adult DE. This dissertation focuses on biological factors as determinants of learning performance. Over the course of 1 year, all new students (N = 4945) of the Open University of the Netherlands were approached. At baseline, 2040 students fully participated in this observational

longitudinal study by filling out an online questionnaire and performing digital cognitive tests. At the 7 and 14 months follow-up, participants filled out a second and third questionnaire, respectively. Data on learning performance were given by the exam registration office. All variables relevant to this dissertation are described in this chapter as well as the design of the investigation. The analyses executed within this dissertation relate to the data collected in the first survey of the ALOUD study. The only exception to this are the additional analyses discussed in box 2 of the discussion which are partially related to data collected in the third survey.

Characteristics of distance education students

Chapter 3 shows that specific student groups in DE, classified as successful, non-successful and non-starting, can be distinguished by different characteristics. This is important as research into these classifications is scarce when it comes to DE. Of the available research, most involves small samples of students and uses persistence and dropout as measures, which are often inconsistently defined making it difficult to compare research findings. This chapter provides a solution to this as a fairly large sample was taken and student groups were clearly defined. The reported characteristics involved measures related to demographics, health, life satisfaction, lifestyle, cognitive performance, study intention, living situation, computer abilities, work, restrictions for learning, and medication use. Descriptives were given for each characteristic and differences between the three groups were tested. Analyses revealed many differences regarding the characteristics between successful, non-successful and non-starting students. Most of the differences found were between the non-starters and the other two student groups. These differences are not extensively discussed here, as the main aim of this dissertation was to predict learning performance. Regarding differences between the successful and the other two student groups, students who were healthy and satisfied with life, were more likely to be successful, as also reflected by a lower body mass index. These differences provide new relevant input for DE institutions and researchers investigating success, persistence and/or dropout in DE.

Biological lifestyle factors predicting learning performance

Chapter 4 presents the results of the analyses regarding the predictive value of the levels of physical activity and sedentary behavior on learning performance. Opposite to the hypotheses, it was found that neither physical activity nor sedentary behavior predicted learning performance. The main explanation for the lack of a relation regarding physical activity is the time restraint DE students experience. DE students often have a partner, children and a job. Because of these responsibilities the time they have left to study is limited. Time spent on physical activity may limit the time left for studying. If too little is learned in the first place, it is impossible for physical activity to stimulate what has not been learned. For sedentary behavior, the main explanation

is that sedentary behaviors were not measured specifically enough to be able to pull apart possible opposing effects of different sedentary behaviors.

Chapter 5 reports on the predictive value of sleep-related variables on learning performance. Analyses revealed that chronotype, sleep duration and/or sleep quality did not predict learning performance. This was partly in line with the hypothesized relations. Chronotype did not predict learning performance, as expected, which provides more evidence for the fact that DE resolves the asynchronous problem which is present in traditional education (Horzum, Önder, & Beşoluk, 2014). Sleep duration was not related to learning performance, neither as a linear term nor as a polynomial term. Sleep quality had no relation with learning performance. Findings on sleep duration and quality were not in line with the hypotheses, which were derived from research in traditional education or research on cognitive performance. For both sleep duration and quality, there is very little research available in this adult population, making it impossible to compare results with previous research. For both sleep duration and quality, it could be that adults are more resilient to sleep deprivation (i.e., following from low duration and/or poor quality) when it comes to learning, compared with children and adolescents, from who the hypotheses were deduced.

Chapter 6 reports on the prediction of learning performance using variables that represent the consumption of caffeine, fish and breakfast. These measures were investigated as they are subjects of interest regarding learning performance in traditional education (Frensham, Bryan, & Parletta, 2012; Owens, Mindell, & Baylor, 2014; Rampersaud, Pereira, Girard, Adams, & Metzl, 2005). As expected, none of the three nutritional measures were predictive for learning performance. It is recommended that future research focuses on the causality of the putative relations by using an experimental design and the evaluation of possible underlying mechanisms (e.g., sleep processes when it comes to caffeine). Second, to evaluate these relations more reliably, dietary patterns must be measured repetitively to make sure intake of nutrients are stable.

Biological lifestyle factors predicting cognitive performance

Chapter 7 reports on the prediction of cognitive performance using the variables measured within the BLFs as determinants. It was shown that sedentary behavior positively predicted processing speed. All other variables related to the BLFs physical activity, sleep and nutrition (i.e., physical activity, chronotype, sleep duration, sleep quality, and the consumption of caffeine, fish, and breakfast) did not predict cognitive performance. The main explanation for this unexpected positive relation is that sedentary behavior in the specific population investigated is most likely mainly characterized by positive sedentary behaviors (e.g., studying or working). Research shows sedentary behaviors to be differently associated with cognition (Kesse-Guyot et al., 2012; Rhodes, Mark, & Temmel, 2012). However, since the specific behavior during the sedentary time was not investigated it is impossible to confirm this possible explanation. Considering this explanation, it is not recommended to be more sedentary.

General discussion

In **Chapter 8** the discussion of this dissertation focuses on three elements: two important concepts are being considered, two possible underlying mechanisms that can explain the hypothesized relations, and new insights regarding the prediction of learning performance. First, some important considerations were discussed around the concept of learning performance and the concept of the assumption that EFs predict learning. Learning performance, operationalized as study progress in chapters 4, 5, and 6, might have been confounded by intention of the student. This confounding could have distorted possible relations. Additional analyses were executed to investigate this potential confounding revealed that this confounding does not seem to be present and that the results found in chapters 4, 5, and 6 seem to be correct. Based on theory, it was expected that EFs mediated a putative relation between variables within the BLFs and learning performance. This assumption of mediation was evaluated in the discussion. First, based on the research conducted in this dissertation, it was concluded that no mediation could be present as both the path between the independent variables (i.e., the BLFs) and the dependent variable (i.e., learning performance) and the path between the independent variables and the mediator (i.e., EFs) were not significant. Second, from the literature reviewed, it seems doubtful whether there is a causal relation between EFs and learning in traditional education in the first place, from which the assumption was derived.

Second, the limitations of the investigation carried out in this dissertation could have prevented possible relations between variables measured within the BLFs and learning performance from emerging. Therefore, despite the fact that no relations were found, two underlying putative mechanisms were discussed. First, interactions of underlying physiological processes resulting from behavior within the BLFs may lead to additive or synergistic effects. Second, epigenetic processes may be important mediating mechanisms in the effects that specific variables within the BLFs have. The general discussion provides a more extensive discussion of these mechanisms.

Last, the execution of this four-year project led to new insights regarding the prediction of learning performance. Basically, the Open University of the Netherlands – who funded this research – would benefit most from research that provides the best prediction model for dropout and success. The findings in this dissertation provide insight on what factors may be important in this respect. With this information, it would be highly attractive to design a second version of the ALOUD study in which the set-up of the study is optimized, using the gained knowledge. Such a new version of the ALOUD project could be highly beneficial for the Open University of the Netherlands. The prediction models, resulting from this project, would provide more information for the Open University of the Netherlands and can assist the institution in tailor-made recommendations for students and tailor-made information for teachers guiding these students.

Concluding, this dissertation provided insight in the characteristics of adult DE students, the prediction of learning performance, and the prediction of cognitive performance, as discussed above. Basically, regarding the prediction of learning performance, the BLFs are not predictive for learning and cognition. However, concerning the limitations mentioned in the general discussion and the respective chapters, it is advised to further investigate the nature of these findings. Nevertheless, if the BLFs are truly not related to learning, this means that generalizing the results found in traditional education among children and adolescents seems not to be a good basis for research in adults participating in DE. These populations of students are probably too different to generalize findings from one population to another.

Regarding the prediction of cognitive performance, it was shown that none of the measures within the BLFs were predictive for performance on EFs. Neither the relation between BLFs and learning performance, nor the relation between BLFs and EFs, was significant. In case EFs mediated a potential relation between BLFs and learning performance, both relations mentioned should have been significant. Thus, it is unlikely that EFs mediated this relation, as the relation itself is lacking in the first place.

In essence, it would be more viable for the Open University of the Netherlands to predict success and dropout from a more general perspective, where all known predictors are taken into account, based on previous research, in order to profit more from research findings. In order to properly set up such research it is advised to use to model of persistence (Rovai, 2003), when it concerns predicting success. For predicting dropout, the review of Lee and Choi (2011) offers a starting point.

SAMENVATTING

Omgevingsfactoren spelen een belangrijke rol bij de ontwikkeling van de cognitieve functies en leervermogens. Tot deze omgevingsfactoren behoren ook de factoren fysieke activiteit, slaap en voeding. Bepaalde aspecten van fysieke activiteit (e.g., actief vs. passief gedrag: Fedewa & Ahn, 2011; Tremblay et al., 2011), slaap (e.g., slaapduur en slaapkwaliteit: Dewald, Meijer, Oort, Kerkhof, & Bögels, 2010) en voeding (e.g., consumptie van ontbijt en vis: Frensham, Bryan, & Parletta, 2012) blijken voorspellend te zijn voor leerprestatie bij kinderen en adolescenten in traditioneel onderwijs. Deze factoren worden biologische leefstijlfactoren (BLF) genoemd. Er is geen reden om aan te nemen dat deze BLF niet voorspellend zijn voor leerprestatie in andere onderwijskundige omstandigheden. Het doel van dit proefschrift is de relatie tussen deze BLF enerzijds en leerprestatie en cognitief presteren anderzijds te onderzoeken in afstandsonderwijs (AO). Dit onderzoek maakt deel uit van het 'Adult Learning Open University Determinants' (ALOUD) onderzoek.

Theoretische achtergrond

Hoofdstuk 1 benadrukt het belang van deze onderzoekspopulatie, namelijk de student in AO. Verder wordt het AO waarbinnen dit onderzoek is uitgevoerd gedefinieerd, alsmede leerprestatie en cognitie. Bovendien wordt uitgelegd waarom dit onderzoek specifiek in AO wordt uitgevoerd en worden de BLF uitvoerig besproken. De veronderstelde mechanismen die verantwoordelijk zijn voor de gevonden relatie tussen de BLF en leerprestatie en cognitie worden behandeld. De doelen van dit proefschrift waren ten eerste het verkennen van de karakteristieken van verschillende studentgroepen (i.e., succesvol, niet-succesvol en niet-startend). Het tweede doel was het onderzoeken of BLF leerprestatie voorspelde. Ten derde werd onderzocht of BLF cognitief presteren voorspelde. Tot slot werd vastgesteld of een mogelijke relatie tussen BLF en leerprestatie werd gemedieerd door executief functioneren (EF).

Opzet van het ALOUD onderzoek

Hoofdstuk 2 beschrijft het ALOUD onderzoek. De relatie tussen psychologische en biologische factoren enerzijds en leerprestatie anderzijds is duidelijk bewezen bij kinderen en adolescenten in traditioneel onderwijs. Desondanks ontbreekt bewijs voor deze relaties in AO voor volwassenen. Het ALOUD onderzoek is het eerste grootschalige onderzoek naar de psychologische en biologische determinanten van leerprestatie in AO voor volwassenen. Dit proefschrift focust op de biologische factoren als determinanten van leerprestatie. In de loop van één jaar werden alle

nieuwe studenten (N = 4945) van de Open Universiteit benaderd. Op baseline namen 2040 studenten volledig deel aan dit observationeel longitudinaal onderzoek door het invullen van een online enquête en het uitvoeren van digitale cognitieve tests. Na 7 en 14 maanden vond een tweede en derde enquête plaats. De data over leerprestatie kwamen direct van het examenregistratiesysteem. Alle variabelen die relevant zijn voor dit proefschrift worden beschreven in dit hoofdstuk, evenals de opzet van het onderzoek. De analyses uitgevoerd binnen dit proefschrift hebben betrekking op de data die verzameld is binnen de eerste enquête van het ALOUD onderzoek. Dit geldt overigens niet voor de aanvullende analyses vermeld in box 2 van de discussie, deze hebben deels betrekking op data verzameld in de derde enquête.

Karakteristieken van studenten in afstandsonderwijs

Hoofdstuk 3 laat zien dat specifieke studentgroepen in AO, geclassificeerd als succesvol, niet-succesvol en niet-startend, verschillen op bepaalde karakteristieken. Dit is belangrijk aangezien onderzoek hiernaar binnen AO schaars is en het meestal groepen betreft die geclassificeerd zijn op volharding en uitval. Deze begrippen zijn vaak erg inconsistent gedefinieerd, wat de vergelijking van resultaten bemoeilijkt. Daarnaast hebben eerdere onderzoeken vaak betrekking op kleine steekproeven. Dit hoofdstuk biedt uitkomst aangezien een relatief grote steekproef genomen is en de studentgroepen duidelijk gedefinieerd zijn. De gerapporteerde karakteristieken betroffen variablen gerelateerd aan demografie, gezondheid, levenstevredenheid, leefstijl, cognitief presteren, studie-intentie, leefsituatie, computervaardigheden, werk, leerbeperkingen en medicijngebruik. Aantallen of gemiddelden voor elke karakteristiek zijn gegeven en de verschillen tussen de drie groepen werden getoetst. Uit de analyses bleek dat er veel verschillen waren tussen succesvolle, niet-succesvolle en niet-startende studenten. De meeste verschillen werden gevonden tussen de niet-starters en de andere twee studentgroepen. Deze verschillen worden niet uitvoerig besproken omdat het hoofddoel van dit proefschrift het voorspellen van leerprestatie is. De verschillen tussen de succesvolle en de andere twee studentgroepen bleken vooral te zitten in gezondheid en levenstevredenheid. Studenten die gezond en tevreden met hun leven waren, hadden meer kans succesvoller te zijn, wat ook gereflecteerd werd door een lagere body mass index. Deze verschillen bieden nieuwe relevante input voor AO instituten en onderzoekers die succes, volharding en/of uitval in AO onderzoeken.

Biologische leefstijlfactoren als voorspeller voor leerprestatie

Hoofdstuk 4 presenteert de resultaten van de analyses over de voorspellende waarde van niveaus van fysieke activiteit en zitgedrag op leerprestatie. In tegenstelling tot de hypotheses werd gevonden dat noch fysieke activiteit, noch zitgedrag leerprestatie voorspelde. De meest voor de hand liggende verklaring voor het gebrek aan een relatie tussen fysieke activiteit en leerprestatie is de tijdsbeperking die studenten in AO ervaren. AO studenten hebben veelal een partner, kinderen en een baan. Door

deze verantwoordelijkheden is de tijd die zij aan studeren kunnen besteden beperkt. De tijd die besteed wordt aan fysieke activiteit kan de tijd die overblijft voor studeren verminderen. Aangezien er in beginsel te weinig geleerd is, kan fysieke activiteit hetgeen dat niet geleerd is ook niet stimuleren. Wat betreft het gebrek aan een relatie tussen zitgedrag en leerprestatie is de meest voor de hand liggende verklaring dat zitgedragingen niet specifiek genoeg gemeten zijn om de mogelijke tegenwerkende effecten van verschillende zitgedragingen uit elkaar te trekken.

Hoofdstuk 5 rapporteert over de voorspellende waarde van slaap-gerelateerde variabelen ten opzichte van leerprestatie. Analyses laten zien dat chronotype, slaapduur en/of slaapkwaliteit leerprestatie niet voorspellen. Dit was gedeeltelijk in overeenkomst met de gestelde hypotheses. Zoals verwacht voorspelde chronotype leerprestatie niet, wat meer bewijs levert voor het feit dat AO het asynchrone probleem dat aanwezig is in traditioneel onderwijs oplost (Horzum, Önder, & Beşoluk, 2014). Slaapduur was niet gerelateerd aan leerprestatie, noch als een lineaire term, noch als een polynomiale term. Slaapkwaliteit vertoonde geen relatie met leerprestatie. Bevindingen over slaapduur en slaapkwaliteit waren niet in overeenstemming met de hypotheses, die afgeleid waren van onderzoek in traditioneel onderwijs of onderzoek naar cognitief presteren. Voor zowel slaapduur als slaapkwaliteit is weinig onderzoek beschikbaar in deze volwassen populatie, wat het onmogelijk maakt om resultaten te vergelijken met eerder onderzoek. Voor zowel slaapduur als slaapkwaliteit zou het kunnen dat volwassenen beter bestand zijn tegen een slaaptekort (i.e., volgend op een te korte slaapduur en/of een slechte slaapkwaliteit) als het aankomt op leren dan kinderen en volwassenen, waarop de hypotheses gebaseerd waren.

Hoofdstuk 6 rapporteert over de voorspelling van leerprestatie aan de hand van variabelen die de consumptie van cafeïne, vis en ontbijt weergeven. Deze variabelen werden onderzocht aangezien deze in traditioneel onderwijs regelmatig in verband worden gebracht met leerprestatie (Frensham et al., 2012; Owens, Mindell, & Baylor, 2014; Rampersaud, Pereira, Girard, Adams, & Metzl, 2005). In overeenstemming met de gestelde hypotheses waren geen van de drie voedingsmaten voorspellend voor leerprestatie. Het wordt aangeraden dat toekomstig onderzoek focust op de causaliteit van de veronderstelde relaties door het gebruik van een experimenteel ontwerp en de evaluatie van mogelijk onderliggende mechanismen (e.g., slaapprocessen wanneer het aankomt op cafeïne). Ten tweede, om deze relaties betrouwbaarder te evalueren is het van belang dat voedingspatronen vaker gemeten worden om er zeker van te zijn dat de inname van voedingsstoffen stabiel is.

Biologische leefstijlfactoren als voorspeller van cognitief presteren

Hoofdstuk 7 rapporteert over de voorspelling van cognitief presteren aan de hand van de gemeten BLF. Er werd aangetoond dat zitgedrag positief voorspellend was voor verwerkingssnelheid. Alle andere variabelen gerelateerd aan de BLF fysieke activiteit, slaap en voeding (i.e., fysieke activiteit, chronotype, slaapduur, slaapkwaliteit

en de consumptie van cafeïne, vis en ontbijt) voorspelden cognitief presteren niet. De meest voor de hand liggende verklaring voor de onverwachte positieve relatie was dat zitgedrag, in de hier onderzochte populatie, waarschijnlijk gekenmerkt werd door positieve zitgedragingen (e.g., studeren of werken). Onderzoek laat zien dat zitgedragingen op verschillende wijze geassocieerd zijn met cognitief presteren (Kesse-Guyot et al., 2012; Rhodes, Mark, & Temmel, 2012). Desalniettemin, gezien het feit dat het specifieke gedrag tijdens het zitten niet onderzocht is, is het onmogelijk om deze verklaring te bevestigen. Gelet op deze verklaring wordt het niet geadviseerd om meer te zitten.

Algemene discussie en conclusie

In **hoofdstuk 8** focust de discussie van dit proefschrift op drie elementen: overwegingen met betrekking tot twee belangrijke concepten, twee mogelijk onderliggende mechanismen die kunnen zorgen voor de relaties gesteld in de hypotheses en nieuwe inzichten voor wat betreft de voorspelling van leerprestatie. Ten eerste worden de overwegingen van twee belangrijke concepten besproken. Dit is het concept van leerprestatie en het concept over de aanname dat EF leren voorspelt. Leerprestatie, geoperationaliseerd als studievoortgang in de hoofstukken 4, 5 en 6, werd mogelijk beïnvloed door de intentie van de student. Deze confounding (i.e., een Engelse term die het proces aangeeft dat een andere variabele het onderzoeksresultaat mogelijk veroorzaakt) kon de mogelijke relaties vervormen. Aanvullende analyses zijn uitgevoerd om deze mogelijke confounding te onderzoeken. Deze lieten zien dat er geen sprake lijkt te zijn van confounding en dat de resultaten gevonden in de hoofdstukken 4, 5 en 6 correct lijken. Gebaseerd op theorie werd verwacht dat EF een mogelijke relatie tussen de variabelen in de BLF en leerprestatie medieerde. Deze aanname werd geëvalueerd in de discussie. Ten eerste, gebaseerd op het onderzoek uitgevoerd in dit proefschrift werd geconcludeerd dat er geen sprake van mediatie kon zijn, aangezien zowel het pad tussen de onafhankelijke variabelen (i.e., de BLF) en de afhankelijke variabele (i.e., leerprestatie) en het pad tussen de onafhankelijke variabelen en de mediator (i.e., EF) niet significant zijn. Ten tweede, de beoordeelde literatuur liet zien dat het twijfelachtig is of er überhaupt een causaal verband is tussen EF en leren in traditioneel onderwijs van waaruit de aanname werd afgeleid.

Ten tweede, de beperkingen van het onderzoek uitgevoerd in dit proefschrift zouden het aantonen van mogelijke relaties tussen de variabelen gemeten binnen de BLF en leerprestatie hebben kunnen voorkomen. Ondanks het feit dat geen relaties gevonden werden zijn om deze reden twee mogelijke mechanismen besproken die de veronderstelde relaties kunnen verklaren. Het eerste mechanisme is de interactie van onderliggende fysiologische processen die volgen op gedrag binnen de BLF dat kan leiden tot additieve of synergistische effecten. Het tweede mechanisme betreft epigenetische processen die mogelijk een belangrijke mediator zijn in het effect dat

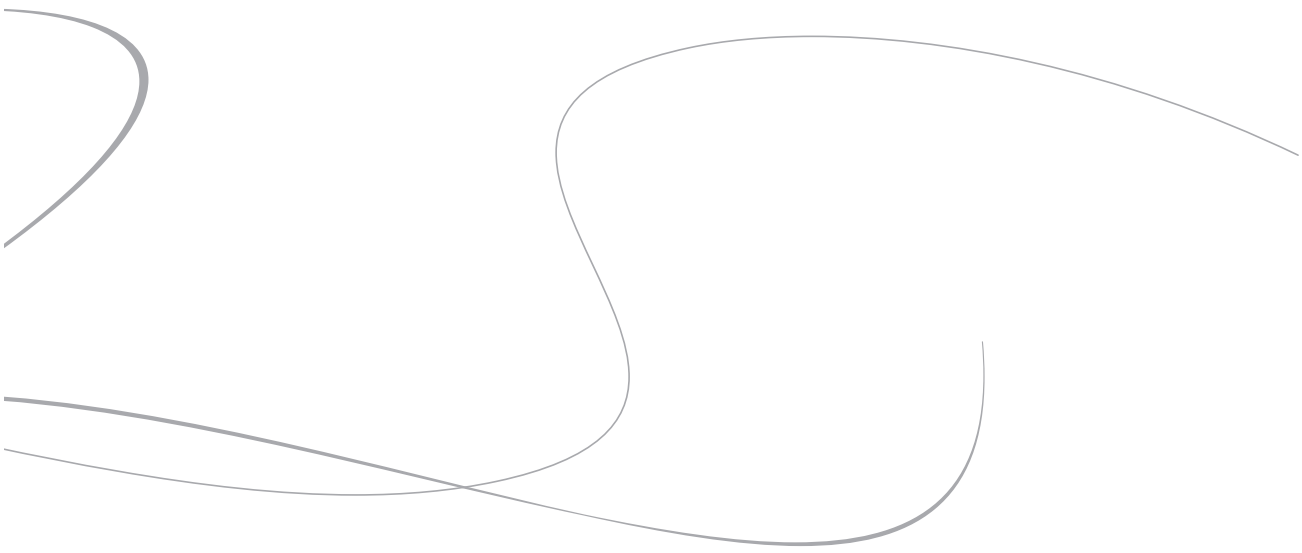
specifieke variabelen binnen de BLF hebben. De algemene discussie voorziet in een meer verdiepende discussie van deze mechanismen.

Tot slot, de uitvoering van dit vier jaar durende project heeft geleid tot nieuwe inzichten met betrekking tot de voorspelling van leerprestatie. In principe zou de Open Universiteit – die dit onderzoek financierde – het meest profiteren van onderzoek dat het beste voorspellingsmodel levert voor uitval en succes. De bevindingen in dit proefschrift leveren inzicht in welke factoren belangrijk kunnen zijn in dit opzicht. Met deze informatie zou het hoogst aantrekkelijk zijn om een tweede versie van het ALOUD onderzoek te ontwerpen waarin de opzet van het onderzoek geoptimaliseerd wordt middels de opgedane kennis. De voorspellingsmodellen die resulteren uit dit project bieden de Open Universiteit en mogelijk andere AO instellingen op maat gemaakte aanbevelingen/informatie voor zowel studenten als voor docenten die de studenten begeleiden.

Concluderend biedt dit proefschrift inzicht in de karakteristieken van volwassen studenten in AO, de voorspelling van leerprestatie en de voorspelling van cognitief presteren, zoals hierboven besproken. Het blijkt dat, met betrekking tot de voorspelling van leerprestaties, de BLF niet voorspellend zijn voor leren en cognitie. Desalniettemin wordt, gezien de beperkingen die besproken zijn in de algemene discussie en de betreffende hoofdstukken, geadviseerd de aard van deze bevindingen verder te onderzoeken. Hoe dan ook, als de BLF daadwerkelijk niet gerelateerd zijn aan leren betekent dit dat het generaliseren van de resultaten gevonden in traditioneel onderwijs bij kinderen en adolescenten blijkbaar geen goede basis is voor onderzoek bij volwassenen studerend in AO. Deze populaties studenten zijn waarschijnlijk te verschillend om bevindingen van de ene populatie naar de andere te generaliseren.

Wat betreft de voorspelling van cognitief presteren is aangetoond dat geen van de variabelen in de BLF voorspellend waren voor prestaties op EF. Noch de relatie tussen BLF en leerprestatie, noch de relatie tussen BLF en EF was significant. In het geval dat EF een mogelijke relatie tussen BLF en leerprestatie medieert, zouden beide relaties significant geweest moeten zijn. Daarom is het onwaarschijnlijk dat EF deze relatie medieert aangezien de relatie zelf überhaupt niet aanwezig is.

In essentie zou de Open Universiteit het meest profiteren van voorspellingen van succes en uitval vanuit een algemener perspectief, waarbij alle bekende voorspellers worden meegenomen op basis van eerder onderzoek. Om een dergelijk onderzoek goed op te zetten wordt aanbevolen het model van volharding te gebruiken (Rovai, 2003), wanneer het om het voorspellen van succes gaat. Voor het voorspellen van uitval biedt de review van Lee en Choi (2011) een startpunt.



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