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Research Article

Collecting and Using Students' Digital Well-Being Data in Multidisciplinary Teaching

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This article examines how students (N = 198; aged 13 to 17) experienced the new methods for sensor-based learning in multidisciplinary teaching in lower and upper secondary education that combine the use of new sensor technology and learning from self-produced well-being data. The aim was to explore how students perceived new methods from the point of view of their learning and did the teaching methods provide new information that could promote their own well-being. We also aimed to find out how to collect digital well-being data from a large number of students and how the collected big data set can be utilized to predict school success from the students' well-being data by using machine learning methods (lasso regression and multilayer perceptron). Results showed that sensor-based learning can promote students' learning and well-being. All upper secondary school (n = 37) and 87% of lower secondary school pupils (n = 161) argued that when data are produced by their bodies, learning is more interesting, and they mostly found that well-being analysis was useful (upper secondary 97%; lower secondary 78%) and can improve personal well-being (upper secondary 78%; lower secondary 67%). The predictive powers with lasso regression and multilayer perceptron (MLP) were quite weak (correlation: −0.14 and 0.34, respectively).

1. Introduction

In recent years, interest in using sensor-based learning technologies in science education has grown [1]. The idea of using wearable sensors has been used for a long time in sports training to give feedback to an athlete, but in the field of education, there have only been some studies [2–4] that explore how new technology could be used as a beneficial educational tool to enhance learning through an authentic learning experience. Self-generated data can be more interesting and more practical for a student than the traditional examples of teaching methods. When the phenomenon is studied with the data produced by students' bodies, it can increase motivation and enhance learning [5]. At the same time, the students learn about their own health behavior. For some students, processing their own data can also increase physical activity [6].

The new wearable technology has evolved enormously over the last few years; it has become more precise and cheaper; its usability has developed; and sensors can be used to collect versatile data about students' well-being, health, and exercise. Best smartwatches can nowadays measure well-being data from the wrist (heart rate, heart rate variability, stress, amount of sleep, steps, calories, exercise load, and VO_2 max-estimation), and they include, for example, accelerometers for movement analysis, location tracking, temperature, and air pressure sensors [7]. The measured data can be analyzed from the perspective of different disciplines in the school [4].

The new Finnish national core curriculums claim that each school has at least one special theme day, a project week, or a special course each year that combines the contents of the different subjects and examines the chosen phenomenon from a multidisciplinary perspective. In multidisciplinary teaching, the same topic or phenomenon is studied from the viewpoint of more than one discipline. The aim was to make it possible for the students to understand relationships and interdependencies between the studied subjects and to help students combine knowledge and skills from different disciplines and structure them into meaningful entities. Multidisciplinary teaching can provide new perspectives for the students which they had never considered before. These episodes are called multidisciplinary learning sets. The learning methods used in multidisciplinary studies emphasize the use of ICT and collaborative learning [8].

With research information, it has become clear that students' overall well-being affects school enjoyment and school performance [9]. The new Finnish national core curriculums for basic education (FNCBE) and upper secondary school emphasize pupils' prerequisites for taking care of their mental and physical well-being, control of everyday life, and use of technology in learning and teaching [8, 10]. The aim was that the pupil learns to take care of him or herself and others and practices the skills that are important to his or her own life and everyday life and increases the well-being of his/her environment. In addition, the pupil should learn to know and understand the factors that promote and contribute to well-being and health and to seek information related to them [8].

The aim of this study was to develop new methods for sensor-based learning in multidisciplinary teaching in lower and upper secondary education that combine the use of new sensor technology and learning from the self-produced well-being data. The main research question is to explore how students perceived new methods from the point of view of their learning and did the teaching methods provide new information that could promote their own well-being? We also studied how to collect digital well-being data from a large number of students and how the collected big data set can be used. There are many possibilities for applying data mining techniques for collected big data, but we chose to examine the methodological objective whether it is possible to predict school success from the students' well-being data by using lasso regression and multilayer perceptron (MLP).

1.1. Well-Being and Learning. Sleep, physical activity, and recovery from stress are fundamental elements for well-being and learning [9]. Recent research has highlighted concerns regarding the well-being of Finnish school-aged adolescents. According to recent surveys, Finnish students move and sleep less than before [11]. In addition, school exhaustion has increased among young Finns. Stress especially affects girls (age: 14–18), of whom 18% feel that they are exhausted. Ten per cent of boys of the same age feel that they are exhausted, but on the other hand, they have more negative attitudes towards schooling. Three-quarters of Finnish upper secondary school students suffer from negative feelings, such as fatigue, stress, anxiety, and boredom, as evidenced by the Finnish Ministry of Education report. Only a quarter of students have positive emotions towards schooling, such as enthusiasm [11, 12]. It is also concerning that Finnish pupils' attitudes towards school have become more negative, and many of them experience a lack of school motivation [13].

The positive effects of sleep and physical activity on children's and adolescents' school performance have been studied [14–18]. The effects of stress on learning results are relatively not studied in adolescents. Stress has both positive and negative effects on learning; stress hormones such as cortisol are good for learning and memory performance, but it is known that prolonged stress has been associated with impaired cognitive performance and has a negative effect on sleep, memory, and learning [19–22]. In this study, we collected pupils' well-being data (e.g., stress, recovery, physical activity, and sleeping time). We used the collected data as learning material and predicted school performance from the measured data.

Stress is a powerful modulator for memory and the process of learning. Acute stress releases stress hormones into the blood that increases arousal, which increases performance up to some point according to the upturned U-shaped curve [21]. This means that memory and cognitive functions will improve as the amount of stress hormones increases to a certain point after which the beneficial effects will become detrimental, and then, a decrease in performance occurs. Chronic stress changes the brain's plasticity and neurogenesis and has harmful effects on the structures of the hippocampus, amygdala, and prefrontal cortex, which can result in memory disorders and mental health problems [20].

The level of stress hormones has a connection with emotional arousal and learning. Several researchers emphasize the significance of emotions in the learning process [23–25]. In learning processes, an optimal level of emotional arousal is necessary. It creates a chemical cocktail in brains consisting of dopamine, noradrenaline, and acetylcholine to keep learners' motivation and attention at the optimum level [26]. A positive feeling strengthens the learning experience and enhances learning [27–29]. Emotions affect the amount of the stress hormone, cortisol, which reinforces the memory trace that emerges through the learning process in the hippocampus [19]. On the other hand, excessive stress and emotional arousal can prevent the effective functioning "thinking part" of prefrontal brain areas important for learning and have a negative effect on learning. When the limbic system, the center of emotional processing, takes control in stressful situations, prefrontal cortex temporarily shuts down [30, 31].

Another perspective for looking at the effects of stress on learning is to study how student experiences the new learning situation, and it depends on students' cognitive abilities and motivation whether the stress in the learning situation is associated with hindrances or challenges. Students who experience challenge stress feel that the learning situation is positive and changeable. Many times, the learning experience is slightly stressed and over-challenged and the student is exposed to something new and these students who experience challenge stress in these situations will more likely cope with their stress and get motivation for learning. According to LePine et al., challenge stress is positively related to motivation to learn and motivation to learn was positively related to learning performance [32]. If the learning task is too challenging in relation to the learner's capacities and resources, it will likely trigger hindrance stress reaction, which is negatively related to motivation to learn [32].

1.2. Measurement of Stress. To collect well-being data and to measure pupils' stress levels and recovery, we used Firstbeat Bodyguard2, which is a heart rate sensor targeted for long-term monitoring of heart rate variability (HRV). HRV is a noninvasive marker of autonomic nervous system (ANS) activity, and HRV-based methods can be used to measure pupils' stress and recovery [33].

Previous studies have measured stress both by subjective and objective instruments. Some studies have been focused on an individual's subjective perception of stress, which can be assessed by using psychological tests and questionnaires [32, 34]. Stress can also be evaluated objectively by measuring the physiological parameters of the body. Stress reaction causes the activation of the sympathetic-adrenal medullary (SAM) system and the hypothalamic-pituitary-adrenocortical (HPA) axis, which elevates blood pressure, heart rate (HR), and concentration of cortisol in blood, urine, and saliva and reduces heart rate variability (HRV) [35, 36]. Measuring cortisol from saliva to assess stress has been used in many studies but it requires a laboratory process and it cannot measure stress levels around the clock. HRV has been evaluated to be most practical method of stress assessment in latest studies [37].

Several studies have found that high psychological stress reduces HRV [38, 39], and HRV has also been shown to be a useful objective method for evaluating the physiological effects of stress [37]. HRV refers to the variation in time between consecutive beats in the heart. A small heart rate variation is a sign of sympathetic activation of the ANS caused by different inherent and environmental stressors. Recovery and restful conditions are linked to increased activity of the parasympathetic part of the autonomic nervous system and higher HRV and lower HR [39].

1.3. Sensor-Based Learning. The collected data can be used for different purposes in sensor-based learning. For example, if the studied phenomenon is stress, the students can then analyze their self-measured stress data to study in which situations they feel stressful and which factors increase their daily stress levels. This can promote motivation for studying the phenomenon, and the obtained data can help them to improve their quality of life and personal well-being. In addition, the same data could be utilized by doctors and school nurses in preventive health care. In the longer term, accumulating big data provide opportunities for data scientists to generate new interesting data-driven hypothesis and develop innovative tools and services for teaching (Figure 1).

Sensor-based science learning by using wearable technologies has been explored in some studies. Some science projects have linked pupils' activity data collected with pedometers and heart rate sensors to learning, and the experiences of both pupils and teachers have been positive [2, 3]. Lee and Thomas [3] used heart rate monitors and pedometers in two fifth-grade classrooms investigating the distances they walk, the relationship between heights and footsteps taken, and variations in heart rates among twins and with adults. From the self-generated data, they learned to draw graphs and tables and compared the differences between different students and considered the reasons. The experimental group had improvement over the leaning results from the control group that used traditional methods. Finn and Mcinnis [2] used wearable technology with fifth- and sixth-grade students. They found that incorporating physical activity into lessons made learning fun and exciting, and it also improved students' scientific investigation skills and graphical analysis and interpretation. It also helped behaviors such as alertness, focus, and concentration.

Moilanen and Salakka [4] used Polar smartwatches with upper secondary school students ($n = 31$) in the advanced physics course 2, which dealt with thermal phenomena, i.e., work, energy, heat, efficiency, and power. The students wore the activity meter on their wrists 24 hours a day during a three-week test period. Finally, the students completed a project task for the course that utilized data collected by the smartwatches. 59 per cent of the students answered in the questionnaire that was held after the course that the use of mobile devices (iPad, smartwatch, and measuring sensors) promoted their learning in physics. A majority of the students in the course wished that smartwatches would be used for physics courses to collect self-generated data for physics assignments. Most of the students also experienced that smartwatch is useful because it motivates to gain physical activity, and it gives useful information about sleeping, activity, and health behavior.

2. Implementation of the Study: Description of Experiments

2.1. Case 1: Lower Secondary School. The study was conducted in a lower secondary school of about 300 pupils in Central Finland. The theme of the school of spring 2017 was taking care of oneself and skills of everyday life. Teachers ($n = 60$) were divided into three teams (X, Y, and Z) in August 2016 for designing a theme day. Each team had representatives from the different subjects, and the teams designed one three-hour learning package, which were held three times during the spring, for about a hundred pupils at a time. The pupils were divided into three groups ($N = 100$), respectively. In the division were taken into account that each group had pupils of all grades.

Teacher team Y planned a workshop that dealt with the theme of sleep, stress management, and physical activity. The pupils were given an opportunity to do Firstbeat well-being measurement and analysis, which offers the pupil individual information about stress factors, sleep, recovery, and movement. The measurements were arranged for the pupils of each group before the theme day. Firstbeat Bodyguard2-sensors were borrowed from Firstbeat and the University of Jyväskylä. The sensors were charged and prepared for pupils for sharing. The package included the sensor, instructions for measurement, and electrodes for attaching the device. The class teacher shared the packages to the pupils two weeks before the well-being theme day in a weekly class meeting and instructed pupils to start

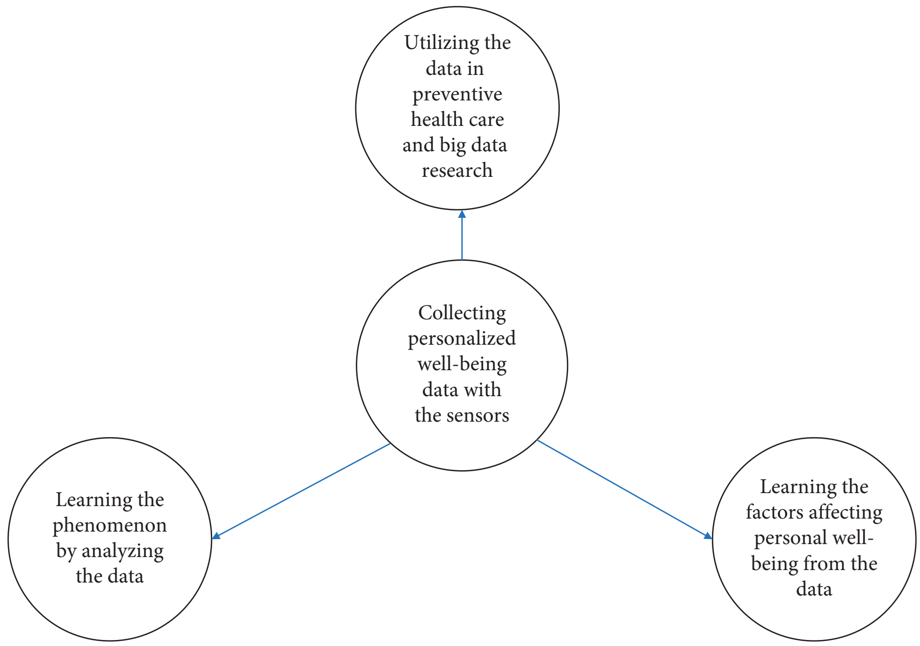

Figure 1: Use of collected data in sensor-based learning.

measurements on Thursday morning and to stop on Sunday morning. This makes it possible to investigate the differences in the pupils' recovery between normal school days and the weekend. The researcher-teacher actively sent reminder messages to the pupils and parents during the measuring process, so that as many as possible could make the measurements before the theme day. The pupils returned the sensors one week before the theme day, so that the researcher-teacher had enough time to upload the data from the sensors to software and prepare the well-being analysis for the pupils.

At the beginning of the theme day, the pupils were divided into three groups, and the pupils received feedback from the well-being analysis. 182 pupils (300 pupils) attended Firstbeat's well-being analysis. The pupils got personal feedback, for example, from different stressors about recovery sufficiency, sleep amount, and quality and about physical activity during the test period. The pupils who did not participate in the well-being analysis formed their own group and filled a multiple-choice questionnaire about their own well-being. Next, each group circulated three functional workshops (duration: 45 min/workshop), where the themes were sleep, physical activity, and stress management.

In the stress management workshop, pupils practiced relaxation skills including simple breathing exercisesand relaxing with music and pictures as well as a short massage session. In addition, pupils were reflecting in the small groups on their own ways to manage stress and shared the practices with the others. In the sleep workshop, the pupils got information about the importance of sleep from the latest research and tools if they had problems with sleeping. In the end of the workshop, pupils responded to the quiz by using an application named "Kahoot." The physical activity workshop combined the use of technology and physical exercise. Pupils among other activities played Just Dance game and Sprint game and practiced the use of Sports Tracker application.

2.2. Case 2: Upper Secondary School—High School: Exercise, Well-Being, and Measuring Course. Initially, in the spring of 2017 and 2018, first was arranged an optional exercise, well-being, and measuring course in the same school. The course included the new Finnish national curriculum multidisciplinary thematic studies for the upper secondary school. The course integrated different disciplines (physics, chemistry, physical education, health education, biology, maths, ICT, and psychology), and themes of the course were physical activity, stress and time management, sleep, and nutrition. The aim of the course was that students measure different physical quantities from their own body and body movement with modern sensor technology and linking the measured data to the studied phenomena. Additionally, the goal was to improve students' well-being with the measured data and feedback from the well-being analysis.

The students got Polar M200 smartwatches for the course, and they did Firstbeat's well-being analysis two times, during the normal school week and during the exam period in the end of the course. They also tested mobile applications for measuring sleep and physical activity.

Sleep and recovery were also possible to monitor with Emfit QS-sleep monitor sensors.

In addition, a large number of students made arterial stiffness measurements, maximum oxygen test capability (VO_2 max), body composition measurements, and the Finnish national physical functional capacity tests for students. A temporary laboratory was built for the course, with which the students could independently or in small groups do some measurements (including blood glucose, PEF, lung volume, hypotension, and hypertension). In addition to normal contact teaching, there were some visits on the course and some visiting experts. Students participated in contact teaching and visits, made measurements, and returned the project work. Five of the eleven tasks from the project work are shown in Table 1.

3. Data Collection, Processing, and Analysis

3.1. Data. The research data were collected at one Finnish University Teacher Training School, and it consisted of three data sets. At the end of the well-being courses, the students responded to an electronic questionnaire. The electronic questionnaire was answered by 198 pupils, and it consisted of Likert-scale questions (5 for strongly agree, 4 for agree, 3 for neutral, 2 for disagree, and 1 for strongly disagree) and open-ended questions that were coded for different subcategories for analysis. The questionnaire was divided according to main research questions as shown in Table 2.

The second data set consists of Firstbeat Bodyguard2-sensor measurements from 112 students between the ages of 13 and 17 (mean: 14.63, std: 1.42). The sensor measurements include 49 physiological variables such as maximum and minimum heart rate, heart rate variability, light and hard exercise time, and stress and relaxation time from the measurement day. Some of the monitored variables, such as HRV, are very individual. Therefore, base values for them should be measured under normal circumstances, and all later measurements proportioned according to those. As the data in this study only included measures from a few days, a change of some variables (standard deviation of RR intervals, min resting heart rate, high frequency power, and low-frequency high-frequency power ratio) between Friday and Saturday was calculated and used. With the change variables, the individual difference does not need to be considered. We had the measurements for 198 students, but finally, the data set consisted only of 112 students, those that had successful measurements from both Friday and Saturday.

The third data set includes all the course grades from the students ($n = 112$), who had a successful Firstbeat measurement. There were 119 variables in the grade data. The grades were combined into an average grade for each student. In addition, the data were normalized to follow the standard normal distribution.

3.2. Data Analysis: Predictive Modelling. For predicting the grades, we used lasso regression and multilayer perceptron (MLP), both with 10-fold cross validation. LassoCV from Python's sklearn library was used, and correlation between the predicted grades and real values was calculated. For MLP, MLPRegressor from sklearn was tested with different parameter values. All available activation functions ("identity," "logistic," "tanh," and "relu") were tested. Solver "lbfgs" (an optimizer in the family of quasi-Newton methods) has been found to perform better for small data sets [40] and was therefore used in this study. A model with one hidden layer with 3, 6, and 9 neurons and regularization terms 0.0001, 0.001, and 0.1 were tested. Again, the correlation between the predicted grades and real values was calculated. We also tried a simpler prediction task, where the students were arranged based on their grade average, and only the best and worst third were included. The task was to predict whether a student belongs to the best or worst third. In addition to prediction, Pearson correlations between the average grades and Firstbeat measurement variables were calculated.

4. Results

4.1. Students' Perceptions of Courses. Figure 2 shows the percentages of students' positive answers to the questions in survey (Table 1). For Likert-scale questions, this means the percentage of the students who answered 4 (agree) or 5 (strongly agree).

In general, students evaluated their experiences of sensor-based learning in both cases positively. All upper secondary school and 87% of lower secondary school pupils argued that when data are produced by their bodies, learning is more interesting, and they mostly found that well-being analysis was useful (upper secondary 97%; lower secondary 78%) and can improve personal well-being (upper secondary 78%; lower secondary 67%). When the students were asked which things/tasks/assignments were the most useful or most effective for their learning, 84 per cent of the students' answers included some of the measurements related to their own body. Lectures held by experts were mentioned in 32 per cent of the students' answers. Some students also argued (8%) that writing the project work of the course was effective for their learning, and 5 per cent of the students' perceived discussion in groups was useful. The students were also asked which of the course's contents were best remembered, and 72 per cent of the students' felt that the measurements were best remembered after the course. Lecturers were mentioned in 36 per cent of the students' responses.

4.2. Data Collection Process. One of the objectives of the study was to pilot how to collect digital health data from a large number of pupils and how to utilize the collected data. The pilot study taught a few important observations about the data collection process. First of all, cooperation with teachers is very important as they help the researcher to share and collect research permissions and sensors in the weekly meetings with their pupils. In our study, the class teacher distributed the sensors to pupils two weeks before the well-being theme day in a weekly class meeting and instructed pupils on the measurements. With lower secondary school pupils, collecting sensors and authorization papers can be sometimes challenging. It took some extra time to send messages to the pupils and parents who had not returned the sensors or permission papers in time. The Finnish school system has a digital Wilma tool for communication with parents, teachers, and pupils, and it made communication easier and faster. We had 30 Firstbeat sensors that were recycled in different groups according to the planned schedule. All the meters were returned in good

Table 1: Five examples of the course tasks.

Stress and recovery Collect from Firstbeat's lifestyle assessment in an excel sheet an average amount of recovery per day as a percentage, length of sleep periods (average for the measurement period), and the amount of recovery from the sleeping period (in per cent). Explain the term "heart rate variability (HRV)" and what does it tell about the autonomic nervous system? What kind of information about body physiology can be obtained when measuring HRV?
Sleep monitoring Collect in an excel sheet an average sleep time/day measured with Polar M200 for the longer measurement period and Firstbeat Bodyguard2 for few days' measurement period. Are there differences in measurements on different devices? What are the consequences of low sleep or poor quality of life? Which stage of sleep is especially important for recovery and learning and why?
Physical activity Collect in an excel sheet an average number of steps per day measured by Firstbeat and Polar devices. What is recommendation and how many steps one should at least take per day? Why long-term sitting makes it harmful and why are more than 20 minutes' sitting time periods should be avoided? Are there any differences between the devices in calculating steps? What was the average calorie consumption per day during measurement period? Were there any differences in calculating energy consumption between Polar's and Firstbeat's devices?
Blood pressure Measure your blood pressure in school's laboratory three times during the normal school day (morning, lunchtime, and afternoon). Do the measurement again on the exam date before the exam. Is there any variation in blood pressure between days and time of day? What is the disadvantage of high/low blood pressure?
Vertical jump Measure three times during the course the maximum height of your vertical jump in laboratory with iPad-video analysis application. Instructions for calculating the maximum height are in the laboratory. Why the Finnish ski team uses the morning vertical maximum jump tests for recovery follow-up?

Table 2: Main research questions and related questions in questionnaire.

Research question	Question in survey/format of the question/data
(1) How did students experience sensor-based learning on the course?	Q1. Which things/tasks/assignments were the most useful or most effective for your own learning? Open-ended question Q2. Which of the course's content was best remembered? Open-ended question Q3. When the measurement data of the course is produced by your own body, it makes the learning phenomenon more interesting. s scale Q4. As things are studied by measuring the quantities of your own body, the things studied will be better remembered. Likert scale
(2) Did the sensor-based teaching methods provide new information that could promote students'well-being?	Q5. Did you get concrete tips on the course that you can improve your overall well-being in everyday life? Likert scale Q6. Firstbeat well-being analysis was, in my opinion, useful. Likert scale Q7. With Firstbeat measurements and results, I can improve my personal well-being. Likert scale
(3) How to collect and utilize digital well-being data from a large number of students?	Teacher-researcher's perceptions
(4) Is it possible to predict school success from the student's well-being data?	Firstbeat well-being data and school grades

condition, and all the pupils got measurements done in time. Measurements were not as successful with all pupils as planned. For some reason, some pupils were wearing the sensor just one day instead for the planned three-day measurement. About 20 per cent of the pupils did not return the permission for the measurements at all, so they could not participate in the measurements and well-being analysis. It is worth thinking about ways for getting these pupils involved in the measurements, because according to the teacher-researcher observations, these pupils had the greatest challenge with health habits and life management, and they might benefit from the measurements most. Pupils in the upper secondary school are in a sensitive and evolving stage of life, so the teachers must be sensitive in all pupils' bodies-related measurements. For example, body composition measurements are not worth doing at all.

With the upper secondary school students, the measurements went smoothly, partly because the students are

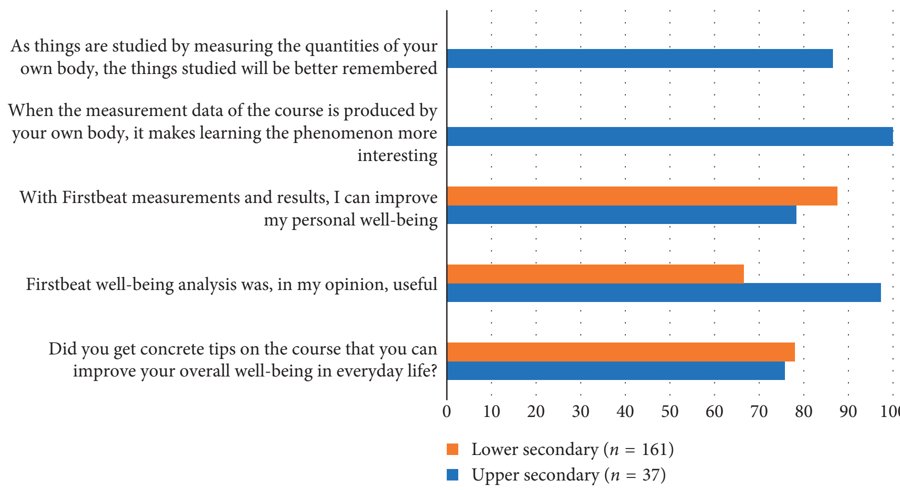

FIGURE 2: Percentages of the students' positive answers to the questions.

more mature, and they chose the course voluntarily. The students used Polar M200 smartwatches and Firstbeat Bodyguard2-sensors for measuring sleep, physical activity, and stress. The usability of the Polar smartwatch was better than the Firstbeat sensor because it measured the data from the wrist. 86 per cent of the students found that the Polar M200 was easy to use. The Firstbeat sensor is attached to the body by electrodes, and 41 per cent of students experienced that wearing it disturbed the everyday life. From the teacher-researcher's point of view, collecting data with Polar was easy. The smartwatches were distributed at the beginning of the course to the students who themselves created user accounts for Polar Flow and paired the watch with their mobile phones, and during the course, they stored their data in the Polar Flow cloud. With Firstbeat sensors, the teacher-researcher had to do all the preparations with the sensors and upload the data after the measurements to the Firstbeat server, where it was possible to create a lifestyle assessment for each student. This process took about 10 minutes per student. Firstbeat sensors are more precise and valid for scientific research than Polar smartwatches, but because of short three-day measurement, randomized factors seem to affect the measurements more than with Polar M200 that were worn many weeks.

4.3. Utilizing the Data Predicting School Success from Well-Being Data. The methodological task of this study was to explore what new information could be processed from the data collected from the students. We decided to find correlation between grades and objectively measured 49 physiological variables by using machine learning. Especially, how the measured stress correlates with school grades is a phenomenon that has not yet been studied.

The correlations between predicted grades and their real values were quite weak. For lasso regression, the correlation was −0.14. In Figure 3, the scatter plot between the true and predicted average grades can be seen. It demonstrates how most of the grades were predicted close to 8.5.

For the tested MLP models, the correlations between the predicted and real average grades are shown in Table 3. The highest correlation was 0.339 with 3 neurons, regularization term was 0.1, and the hyperbolic tan function ($f(x) = \tanh(x)$) as activation. The scatter plot for real and predicted grades is shown in Figure 4.

In the simple task, where the aim of the prediction was to decide whether a student belongs to the best or worst third, MLP classified about 46% to the wrong class. When calculating the correlations between the variables, a significant correlation (−0.267, $p < 0.01$) was found between carbohydrate energy expenditure (EECH) and the grade average. However, this may just be a coincidence as there were 49 correlations calculated, and therefore, the p value should be corrected accordingly.

5. Conclusions and Discussion

The focus of the pilot study was to explore how pupils experience sensor-based learning with the data produced by their own bodies. Because research was restricted to one school, the results can be generalised only after further studies in other environments. However, the findings provide measured data that can be utilized in developing teaching practices in compliance with the new national core curriculum in Finnish schools.

As a whole, the pupils experienced sensor-based leaning as a positive learning experience and felt that it promoted their learning, and most of them thought obtained data can improve their personal well-being. Tulving et al. [38] found that learning of objective data or "facts" will be enhanced if the learning process involves personal or emotional factors. Kolb [39] emphasizes the experience as a basis for learning. Action-based learning processes involve emotions and use of different senses and enable a meaningful learning experience to emerge [39]. This pilot study suggests that the sensor-based learning methods increase meaningfulness in learning. PISA 2015 [41] results highlighted that Finnish boys' motivation in science had lowered. It may thus be that traditional science teaching methods do not stimulate boys' interest in the studied content. Further research should be

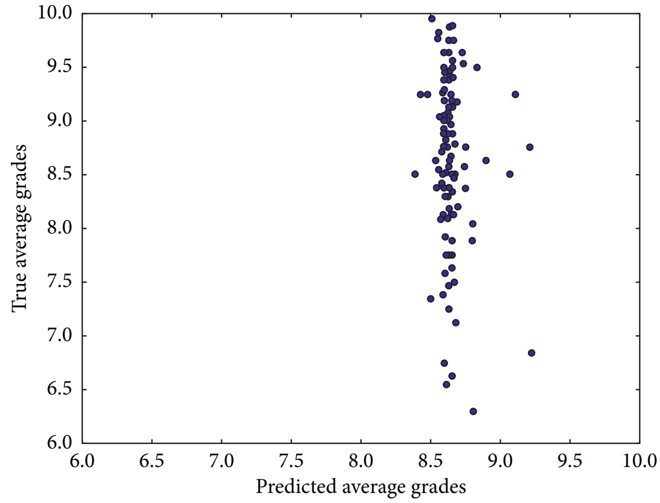

Figure 3: The true and predicted average grades with lasso.

Table 3: Correlation between predicted and real grades for different MLP models.

Neurons	3	3	3	6	6	6	9	9	9
Regularization	0.0001	0.001	0.1	0.0001	0.001	0.1	0.0001	0.001	0.1
Identity	0.051	0.046	0.211	0.058	0.061	0.211	0.067	0.059	0.211
Logistic	0.154	0.243	0.090	0.157	0.151	0.088	0.123	0.127	0.184
Tanh	0.148	0.190	**0.339**	0.140	0.140	0.218	0.012	0.018	0.122
Relu	0.141	0.046	0.058	−0.033	−0.063	0.013	−0.134	−0.133	−0.054

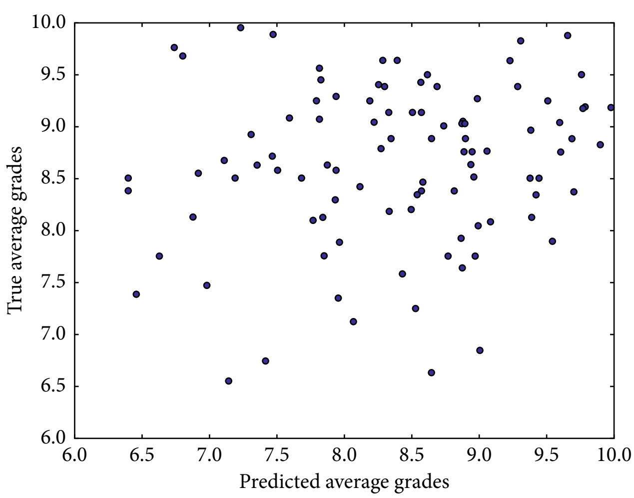

Figure 4: The true and predicted average grades with MLP.

conducted in order to find out whether girls and boys experience bodily learning methods in different ways and whether especially boys could benefit from the sensor-based approach in science.

In the responses from the students, the course measurements were positively emphasized. Measurements at the course were bodily active processes that combined the cooperation and the use of different sensory channels. When both different senses and the body participate in the learning process, more persistent memory traces can emerge [42, 43]. This supports the view that most pupils benefit from the use of body and several sensory channels in instruction [44, 45].

Sensor-based learning featured various elements that differed from the elements of regular courses, for instance, the new sensor technology, bodily approach, a learning environment outside of the classroom, and visiting lecturers. Breaking the routine regarding teaching methods, learning environments, or tools increases pupils' attention and contributes to a memorable learning experience [4, 46]. It can be hypothesised that pupils tend to find a change in working methods positive, so the positive findings of the study are no surprise in this respect. Therefore, further research should be conducted to find out pupils' experiences of long-term use of the sensor-based learning methods.

Research has found that self-tracking technology can improve an individual's well-being and motivation toward exercising on the short term, but there are challenges in acceptance and long-term use of wearable self-tracking technology [47–50]. Even though the pupils felt that the measurements were beneficial for their well-being development, further studies should investigate whether the measurements will cause permanent changes in health habits.

This pilot study is a part of the University of Jyväskylä project, which aims to explore the use of big data and artificial intelligence in health care and education (Figure 5) [47]. Self-quantification, artificial intelligence, and telemedicine will bring savings in health care in the future [47]. The Finnish education system produces a huge amount of data that is not yet utilized in preventative health care. We find that the same digital well-being data could be utilized both in learning and in preventive health care. In future, the

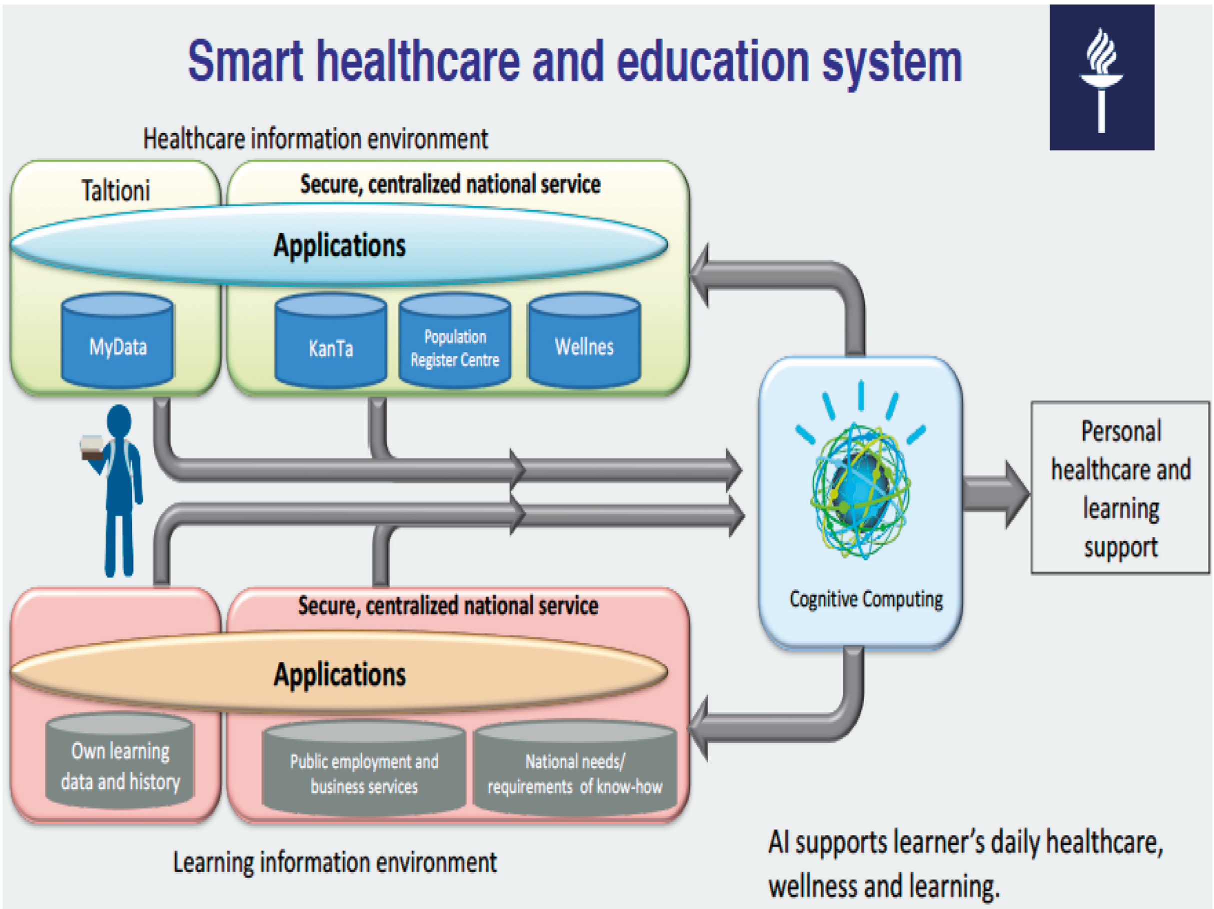

Figure 5: Cognitive computing in Finnish smart health care and education system in the future [51].

role of schools in preventative health care is emphasized. Health-measuring technology is developing at a rapid pace and becoming more reliable, cheaper, and easier to use. This is also open for schools providing new types of opportunities for the exploitation of health data [51]. Properly utilized measurements can give students valuable information about themselves and evoke the interest in their own health behavior as well as how the student's own actions affect body and mind. Well-being guarantees better conditions for learning. We found that the collection of well-being data was successful with a reasonable amount of work, and in future research, we aim to collect more data sets which also include data from blood samples. However, it is important to remember that ethics and security in data management are the most important factors in data collection process.

According to the experiences of the students, the collection of the well-being data should be easy and effortless. Nowadays, heart rate variation can be measured from the wrist, so in future research, data could be collected with smartwatches, rings, or clothes. This would facilitate data collection and allow a longer measurement period, and the sensors would be more comfortable for the user.

One of the aims of this study was to examine whether it is possible to find correlations between the physiological variables of sensor measurements and school grades and to predict school success from well-being data. The weak correlations in prediction are most probably related to the data properties and not the predictive power of Firstbeat's well-being measurements. In further studies, a longer measurement period could provide more accurate information. Additionally, a more reliable picture of exercise habits, recovery, and their individual impact would be obtained. In this study, randomized factors seem to affect the measurements during the three-day measurement period. At the individual level, measurements could be made several times, for example, during the exam week, in order to follow the development of well-being factors over the long term.

Data Availability

The students' well-being data, grades, and answers to the electronic questionnaire data used to support the findings of this study are restricted by the University of Jyväskylä Ethical Committee principles in order to protect students' privacy. Data are available from Hannu Moilanen (University of Jyväskylä), for researchers who meet the criteria for access to confidential data.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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