Ella Mäkelä

DECORATIVE IMAGES' EFFECT ON THE COGNITIVE LOAD OF COMPUTER PROGRAMMING LEARNING

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Kognitiivinen kuormitusteoria pyrkii kehittämään ohjeistuksia, jotka helpottavat oppimisen aikana koettavaa henkistä kuormitusta. Useita periaatteita on kehitetty kognitiivisen kuormituksen luontaisten, ulkoisten ja hyödyllisten piirteiden hallintaan. Tavat vähentää ulkoista kuormitusta kohdistuvat usein oppimateriaalin ulkonäöllisiin ja rakenteellisiin piirteisiin. Kuvien on todettu joko edistävän tai heikentävän oppimista niiden tarpeellisuuden mukaan. Koristeelliset kuvat motivoivat oppijaa ja tekevät oppimistilanteesta mieluisamman. Tutkimustieto ei kuitenkaan ole samaa mieltä kuvituskuvien vaikutuksesta varsinaiseen oppimiseen. Aikaisempaa tutkimusta kuvituskuvien vaikutuksista ohjelmoinnin oppimiseen ei ole tehty. Tämä tutkimus pyrkii selvittämään, miten asiayhteyteen liittyvät kuvituskuvat vaikuttavat olio-ohjelmoinnin oppimisen kognitiivisen kuormitukseen noviiseilla oppijoilla. Tulokset näyttävät, että kuvituskuvilla ei ole merkityksellistä vaikutusta opiskelijoiden kokemaan kognitiiviseen kuormitukseen. Tutkimuksessa havaittiin keskikokoinen korrelaatio tehtävistä suoriutumisen ja kognitiivisen kuormituksen välillä. Tulokset osoittavat, että kognitiivista kuormitusteoriaa voidaan hyödyntää myös ohjelmoinnin oppimateriaalien suunnittelussa. Ohjelmointi on monitahoinen kokonaisuus, jonka oppimateriaalien ja kognitiivisen kuormituksen yhteyttä tulisi tutkia enemmän.

Asiasanat: kognitiivinen kuormitusteoria, oppimismuotoilu, olio-ohjelmointi

ABSTRACT

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Cognitive load theory aims to develop instructional materials that manage learners' mental effort used during learning. Many principles have been developed to aid in managing its intrinsic, extraneous, and germane features. Methods for reducing extraneous load often assess the visuality and structure of the learning material's elements. Images have been found to either promote or hinder learning depending on their redundant nature. Decorative images have been found to motivate students and make the learning experience more enjoyable. There is however contradicting research on their effects on actual learning. No prior research has been done on decorative images' effects on computer programming learning. This study aims to find how decorative, context-specific images affect the cognitive load of object-oriented programming learning for novice students. The results show that decorative images have no significant effect on the cognitive load experienced by learners. A medium-sized correlation between task performance and cognitive load was observed. The results indicate that cognitive load theory can be utilized also in the design of computer programming materials. As computer programming can be considered to be complex learning, more research should be conducted on cognitive load and its implications for computer programming instructional materials.

Keywords: cognitive load theory, instructional design, object-oriented programming

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1 INTRODUCTION

Effective learning materials do not make learning exhausting for students. If the cognitive load of learning material is high, actual learning might not happen. Managing the natural complexity of the instructional material in addition to minimizing the cognitive load imposed by the visual and structural parts of the material is essential for promoting learning. Reducing useless cognitive load lets students allocate more effort to learning. Redesigning instructional materials to manage cognitive load is the main goal of cognitive load theory (Sweller, 1988).

Online learning or e-learning has become an integral part of education and its adoption has been accelerated by forced remote learning during the COVID-19 pandemic. E-learning materials and teaching online however require more research and effort to implement designs proven effective (Teräs et al., 2020; Vergara et al., 2022; Zhu & Liu, 2020). Higher education might have been too fast in implementing their learning materials online and experienced difficulties in providing pedagogically sound learning experiences due to lacking resources (Crick et al., 2020). Educators have limited resources compared to their workload (Ylijoki, 2013) and worry about how e-learning will affect it further (Crick et al., 2020). Effective and easy-to-implement e-learning design principles should be developed and studied in order to ease the burden of creating usable online materials put onto educators.

Images are easy to source and place on online learning materials. They could provide a practical way of introducing multimedia to static e-learning materials without too big of a workload. Decorative images have been found to motivate students and create a more positive learning experience (Carney & Levin, 2002; Lenzner et al., 2013). Research on how decorative images affect computer programming has not been done before.

This paper examines the effects decorative, context-specific images have on cognitive load experienced during learning computer programming. It will cover the essentials of cognitive load theory and instructional design before presenting the implemented study and its results. The paper will end with conclusions and limitations covering the summary of results and reliability of the research.

2 THEORY AND RELATED WORK

Relevant previous studies of cognitive load theory and instructional design will be presented here in order to fully understand the implications this research makes. Cognitive load theory will be covered through its three categories of intrinsic, extraneous, and germane load in addition to briefly explaining ways of measuring cognitive load. The chapter Instructional theories and models will present briefly some learning theories and instructional models as well as discuss e-learning and decorative images in learning. Lastly, the chapter Cognitive load theory in e-learning materials will present four instructional design guidelines based on CLT and e-learning and summarize the principles presented in them.

2.1 Cognitive load theory

Cognitive load means the mental workload humans need to carry out tasks. The term can be connected to the discovery that humans have a limited working memory which presents itself as a limitation to information processing and in turn learning (Miller, 1956). The beginnings of utilizing cognitive load in learning material design are in the late 1980s and early 90's when the article Cognitive Load During Problem Solving: Effects on Learning (Sweller, 1988) was published and Sweller began his extensive research with colleagues. Sweller found that the cognitive load required by conventional problem solving, in this case having a specific goal to achieve, intervenes with learning. In his subsequent paper he suggests that in addition to not using conventional problem solving but instead formats such as goal-free problems, the learning material's format itself should support knowledge acquisition by minimizing needed cognitive load (Sweller, 1988, 1989).

The two papers by Sweller (1988, 1989) were the beginning of Cognitive Load Theory (CLT). CLT implies that instructional material should be designed to minimize the required cognitive load to facilitate learning. In simpler terms, when solving a problem takes up too much mental capacity, there is not enough room to transfer knowledge to memory. Cognitive Load Theory is used specifically when talking about instructional design's relationship to cognitive load and should not be confused with the general terms of Cognitive Load or Mental Workload used for mental effort.

Early research on CLT focused on the split-attention effect, redundancy effect, schema acquisition, and rule automation. The split-attention effect happens when learning material's two or more mutually dependent materials are split, e.g. diagram's labels are based below the diagram rather than within it and learners need to mentally integrate them to fully understand the topic (Bobis et al., 1993; Chandler & Sweller, 1991, 1992; Sweller, 1989, 1993; Sweller et al., 1990; Tarmizi & Sweller, 1988; Ward & Sweller, 1990). The redundancy effect is present when the same information is explained simultaneously with different formats or excessively (Bobis et al., 1993; Sweller, 1993). Schema acquisition is a way of understanding learning as acquiring patterns and rules (Sweller, 1988, 1989, 1993; Tarmizi & Sweller, 1988; Ward & Sweller, 1990) that can be later instinctually utilized by rule automation (Sweller, 1989, 1993).

In the last ten years cognitive load theory has become a tool to study and develop new innovative learning formats like educational computer games (Hwang et al., 2013), flipped classroom (Abeysekera & Dawson, 2015), educational videos (Brame, 2016), virtual reality learning (Makransky et al., 2019) and online learning (Mukhtar et al., 2020).

Early on research started to focus on specific types of cognitive load. The cognitive load imposed by the representation of the problem, or extraneous cognitive load, was first introduced when studying the effect learning materials' structure had on learning (Sweller et al., 1990; Sweller & Chandler, 1991; Tarmizi & Sweller, 1988). When doing research on extraneous cognitive load it had to be considered how much of cognitive load was by the materials' extraneous aspects and what was imposed by the problems' difficulty itself. The problems' inherent complexity was studied as intrinsic cognitive load (Bobis et al., 1993; Sweller, 1994; Sweller & Chandler, 1991). Later, the positive mental effort that encourages learning was introduced as germane cognitive load (Mwangi & Sweller, 1998; Sweller et al., 1998). Intrinsic, extraneous, and germane cognitive loads will be discussed further in the following chapters.

2.1.1 Intrinsic cognitive load

Intrinsic cognitive load is created by the problem's innate complexity, which in turn is determined by element interactivity. The elements of the learning material are interacting with each other if they cannot be learned without attending to them simultaneously. High interactivity results in high task complexity and high intrinsic cognitive load. (Sweller, 1994). Intrinsic cognitive load can be defined also to depend on the learner's prior knowledge. The severity of element interactivity is subjective. Some learners may have acquired schemata that allow them to process multiple element relationships automatically and so perceive less element interactivity (Ayres, 2006; Renkl & Atkinson, 2003).

It was previously thought that intrinsic cognitive load cannot be manipulated. This was due to the idea that it is completely defined by the element interactivity and the learner's previous knowledge. (Sweller et al., 1998; Sweller

& Chandler, 1994). Managing intrinsic cognitive load by means of instructional design has become a new area of study within CLT. Summarized by Schnotz & Kürschner (2007) intrinsic cognitive load, or task difficulty, can and should be managed to not be too high or too low. Many new approaches to reducing intrinsic cognitive load use some sort of sequencing of the instructional material (Gerjets et al., 2004; Kester et al., 2006; Pollock et al., 2002; Renkl & Atkinson, 2003).

The expertise reversal effect has proved that in some circumstances thorough and detailed instructional material designed for novice learners imposes a heavier cognitive load on more experienced learners. Expert learners must analyze the given information, redundant to them, against their prior knowledge which puts more pressure on the working memory. The expertise reversal effect emphasizes the need to tailor learning material to the learner's level (Kalyuga et al., 2003).

Renkl & Atkinson (2003) suggest gradually introducing problem solving after first studying the initial example. With this strategy called fading, learners would first study the complete example (model) and then an example with a part omitted (coached problem solving). Gradually the number of omitted parts increases until there is only left the whole problem (independent problem solving). This method gradually decreases intrinsic cognitive load by means of cognitive skill acquisition and allows an increase in the complexity of problem-solving tasks without heavy cognitive load. Renkl & Atkinson's study also supports the expertise reversal effect.

Gerjets et al. (2004) have a modular approach to decreasing intrinsic cognitive load. They suggest breaking down solution procedures into smaller ones that can be understood separately. They found that this approach is effective for learners with different levels of prior knowledge and is stable with a variety of instructional conditions.

Pollock et al. (2002) suggested an isolated-interacting elements instructional method that tries to combat element interactivity directly. The approach requires the material to be first learned in smaller isolated parts. This lessens the amount of information being held and cross-referenced in working memory. In contrast to Gerjets et al. modular approach isolated-interacting elements instructional method doesn't require the smaller parts to be fully understood independently. After the singular parts have been studied, their relationships are revealed and the whole of the topic will be understood completely (Pollock et al., 2002). With the isolated-interacting elements instructional method understanding of complex topics had been observed to be higher compared to students who had all the information presented to them simultaneously and repeatedly (Lu et al., 2020; Pollock et al., 2002).

2.1.2 Extraneous cognitive load

The effect extraneous components of learning material have on cognitive load is dependent on the level of the material's intrinsic nature. It is imposed by the learning material's design and structure. The more complex a problem is the more meaningful minimizing extraneous cognitive load is (Sweller, 1994).

Element interactivity, which is a key element defining intrinsic cognitive load, can also be due to the manner of presentation. If the information representation is faulty of high element interactivity, it can be reduced by restructuring (Sweller, 2010). The goal for restructuring is to facilitate schema acquisition and automation (Sweller & Chandler, 1994; Van Merriënboer et al., 2002). Reducing extraneous load and increasing germane load facilitates putting propositional knowledge into action and acquiring schemata. Extraneous load while studying complex information can be reduced by applying instructional designs proven effective and combining them with complementary teaching. Removing split-attention and redundancy effects have been proven to be effective design choices for reducing extraneous cognitive load (Pociask & Morrison, 2008).

Extraneous cognitive load can be the result of four types of mistakes in extraneous structures of the material: 1) high element interactivity, 2) unnecessary efforts to maintain relevant information in working memory, 3) enforced interactivity of irrelevant information or 4) waste of time and effort on too easy tasks or unneeded instructional help (Schnotz & Kürschner, 2007). Some methods of assessing these problems are presented here.

Completion problems are a method of lowering extraneous cognitive load by providing a problem statement with a partial solution of it that then should be completed by the learners. The method has been found to be useful for novice learners and has a positive effect on far transfer. Far transfer is when learners are able to utilize previously learned knowledge later in a different problem scope than where they learned it from (van Merriënboer et al., 2002).

One approach to reducing extraneous cognitive load is to determine if the redundancy effect is present. Removing redundant information is beneficial for limiting cognitive load but learning material designers should be considerate when reducing information to not reverse the desired effect (Antonenko & Niederhauser, 2010; Bobis et al., 1993; Pociask & Morrison, 2008).

Antonenko & Niederhauser (2010) studied the effect of lead-augmented conditions on extraneous and germane load. Leads are previews of link contents that can be accessed without leaving the current page. Leads have been thought to be effective also in encouraging learners to relate new information to their prior knowledge and therefore activating relevant representations from long-term memory. Utilizing also long-term memory bypasses some of the use of short-term memory and increases germane processing. They also prepare learners for upcoming information without leaving the current position in the material. This limits the split-attention effect, compared to having to open links in between reading, and improves structural and domain learning. Leads might however make reading times longer (Antonenko & Niederhauser, 2010). Wikipedia for example implemented leads of internal links as summaries of the contents that show up when hovering over the link. Leads can also be seen on social media platforms like Facebook, Twitter, and LinkedIn which provide a small preview of the linked site at the end of a post.

Salden et al. (2010) found that computer-based tutors can support learning by offering individualized methods of selecting appropriate problems to solve, following student-specific alternative solution strategies, providing step-by-step feedback, and giving context-specific hints and examples of next steps. Cognitive computer tutors reduce extraneous cognitive load by defining a smaller area of the learning material from which students must search to find the information needed to solve problems. They also found a positive effect of combining worked examples and computer tutoring.

2.1.3 Germane cognitive load

Germane cognitive load facilitates learning as it is defined as the effort required for acquiring schemata. It is thought that learning happens as long as the sum of the learning material's intrinsic and extraneous cognitive load and the germane cognitive load needed for schema acquisition do not exceed working memory. When there are significant amounts of intrinsic and extraneous load, working memory can be overloaded and not much is left for germane load. This can result in minimal or nonexistent learning (Ayres, 2006; Renkl & Atkinson, 2003; Sweller et al., 1998). Kalyuga (2011) argued against the well-established existence of germane cognitive load. They believe the distinction between intrinsic and germane load in traditional views of cognitive load theory is not clear. Intrinsic load is considered to be from how complex the subject matter is to learn while germane load is considered to be from the activities used to learn the learning material. Kalyuga proposes to revert to the framework of having only intrinsic and extraneous cognitive loads. The germane load, or any activities related to actual learning, would be combined with intrinsic cognitive load.

Increasing germane cognitive load is often done by decreasing extraneous and sometimes intrinsic cognitive load. Combinations from all the available methods of managing germane and extraneous load should be studied to find the most suitable one (van Merriënboer et al., 2002). Some studies that combat promoting germane cognitive load directly are presented here.

Renkl & Atkinson (2003) argue that once knowledge is acquired examples and self-explanation strategies transfer from germane to extraneous cognitive load. Schema acquisition allows learners to focus on speed and accuracy and strive for automation and going through redundant examples becomes burdensome. This is why Renkl & Atkinson encourage to not introduce problem-solving too late.

High contextual interference is when the structure for learning skills doesn't follow a logical order of simple-to-complex but instead different levels of information and problems are presented in a mixed order. This method has been found to increase the germane load for experienced learners as has been variability in presentation formats, asking learners questions to increase their depth of processing and provoking group discussions (van Merriënboer et al., 2002).

The variability effect has been found to affect extraneous cognitive load negatively while also increasing germane load. The positive effects of higher germane load overpower the negatives of increased extraneous load. Variability within learning materials can be done by for example having different kinds of problems and themes, changing the visual presentation of the material, and the time and place of instruction (Likourezos et al., 2019; Lu et al., 2020; Paas & Merrienboer, 1994; Sweller et al., 1998; van Merriënboer et al., 2006). Germane load can also be affected by giving learners power over their preferred problem formats (Van Merriënboer et al., 2002).

Germane load becomes increasingly important when learning complex materials, such as real-life tasks. Van Merriënboer et al. (2006) suggest a two-stage approach to tackle complex learning: 1) decrease the intrinsic load by limiting element interactivity, 2) increase the germane load with methods like the variability effect.

Cheon & Grant (2012) found that metaphorical interfaces promote schema acquisition and automation. In other words, combining the learning material and user interface by reflecting the topic being learned within the UI elements has a positive effect on germane cognitive load.

2.1.4 Measuring cognitive load

To make use of cognitive load theory researchers started to develop tools to measure it. The first and still widely popular cognitive load measurement tool was developed by Paas in 1992 (Klepsch et al., 2017; Sweller et al., 2019). Paas developed a single-item 9-grade symmetrical scale to measure the mental effort of single statistics problems. The scale was found to be a successful and sensitive subjective rating scale for cognitive load (Paas, 1992). Paas' scale as well as other single-item scales seem very convenient from the researchers' and subjects' points of view but have been critiqued for their problematic reliability and incapability of differentiating between different types of cognitive loads (Klepsch et al., 2017; Leppink & Pérez-Fuster, 2017; Sweller et al., 2019). Other subjective rating scales have emerged since Paas'. Leppink et al. (2013) tackled the problem of measuring the multiple types of cognitive load. Their ten-item 10-grade scale questionnaire was later modified by Morrison et al. (2014) for measuring the cognitive load of computer science education. Klepsch et al. (2017) developed two rating scales, naïve and informed, for measuring all three types of cognitive load differentially. The naïve rating is a self-report Likert questionnaire with items relating to each type of cognitive load. The informed rating requires participants to first learn and understand cognitive load theory and its three types. They are then equipped to evaluate their perceived cognitive load with questions directly referring to each type of cognitive load by their name ("During this task extraneous load was…"). Schmeck et al. (2015) found that when using subjective cognitive load rating scales, estimating cognitive load with a single scale at the end of a series of tasks (delayed) results in a higher perceived cognitive load than what would be each task's mean rating (immediate).

Objective measures, such as secondary tasks and physiological measures, have become increasingly studied in the area of CLT (Sweller et al., 2019). Secondary tasks have been found to be effective in sensing cognitive load (Haji et al., 2015; Park & Brünken, 2015). The performance of completing or keeping up with a secondary task simultaneously with the primary task can be analyzed to deduce the primary task's cognitive load. Examples of secondary tasks are rhythm or tapping tasks such as tapping a predetermined rhythm with feet throughout the primary task (Park & Brünken, 2015), stimulus-monitoring tasks such as pressing a button every time a vibration is felt on legs (Brünken et al., 2004; Cierniak et al., 2009; Haji et al., 2015) or mental tracking tasks such as reciting a previously showed letter while simultaneously memorizing the next letter (Chandler & Sweller, 1996). Pupillary movements have been proven to correlate with cognitive load. When the load in memory is increasing so is the diameter of the pupil. Pupil movements have been studied as task-evoked pupillary responses (Beatty, 1982; Duchowski et al., 2018; Klingner et al., 2008). Pupillary movements have been measured by head-mounted trackers. Remote video eye trackers have also been found to have the required precision, making eye-tracking more comfortable for participants (Klingner et al., 2008). Remote video measurements of breathing and heart rate variability were found to also indicate changes in cognitive load (McDuff et al., 2014; Nicolò et al., 2020).

Learners' prior knowledge affects cognitive load, especially intrinsic load, and thus learning materials should be modified to meet the level of expertise. Kalyuga & Sweller (2004) developed a rapid method of measuring learners' levels of knowledge in a specific area. The students were asked to write only the next step in a couple of given problems in a very short period. The level of knowledge was determined by the completion time and success of the tasks. The rapid test was found to be an effective tool for evaluating learners' level of knowledge and utilized in adapting learning materials to manage cognitive load.

2.2 Instructional theories and models

Teachers, educators, and instructors planning and creating instructional materials should understand learning theories and instructional design principles to assist learners to reach their learning goals. Being able to create effective learning materials is crucial for a positive learning experience for students and teachers alike. (Ertmer & Newby, 2013; Khalil & Elkhider, 2016).

Learning theories can be divided into at least three categories of behaviorism, cognitivism, and constructivism. Behaviorism is focused on how learning is encouraged with cues, practice, and reinforcement. Cognitivism puts emphasis also on learners' cognitive processes that support acquiring knowledge. (Ertmer & Newby, 2013). Both behaviorist and cognitivist approaches to instruction can be put under the umbrella of instructivism, which promotes the instructors' role in deciding what is taught and how (Khalil & Elkhider, 2016). Behaviorism considers the learner a passive agent reacting to stimulus from the environment while in cognitivism learners are considered to take an active part in the whole process. Constructivism is thinking that learning is creating meaning from experience and elaborating and interpreting information even further. Like cognitivism, or even more so, constructivism believes learners are an active part of the learning process (Ertmer & Newby, 2013).

Instructional models are guidelines created to help apply learning theories to learning materials and ensure informed and effective design. Most instructional models have some key principles in common. Learning is thought to happen when 1) real-world problems are solved, 2) prior knowledge is utilized, 3) new knowledge is demonstrated, 4) new knowledge is applied, and 5) new knowledge is integrated (Merrill, 2002). A few instructional design models are briefly presented next.

ADDIE is an instructional design model that follows five steps of analyze, design, develop, implement, and evaluate (Branch, 2009). The ADDIE model is the most used among instructional design professionals for its simple and straightforward structure that is easy to learn and implement (Khalil & Elkhider, 2016). The Dick and Carey method is a nine-step process that consists of all the same principles ADDIE described but in more detail. Both ADDIE and the Dick and Carey method have a behavioral approach (Khalil & Elkhider, 2016). The 4C/ID -model developed by van Merriënboer et al. (2002) combats complex learning by describing four components of learning environments 1) learning tasks, 2) supportive information, 3) just-in-time information, and 4) part-task practice. The 4C/ID -model has a background in constructivism and instructivism. It emphasizes managing the cognitive load of learners by presenting suggestions for better design of the four identified components. The method is targeted for the transfer of complex skills in complex learning modules (van Merriënboer et al., 2002).

2.2.1 E-learning materials

E-learning, online learning, and distance learning are not synonyms for learning that happens online. People in different institutions and areas can define them differently and hence it is important to differentiate them (Moore et al., 2011). In this paper e-learning and online learning are used interchangeably. The terms are used to express learning that happens using learning materials found online. These situations can be done independently without any connection to an instructor or in an online-course situation where learners can contact and talk to an instructor either in compulsory lessons or when needed. Such learning experiences can be for example university online courses, MOOCs, open online courses, or learning independently from online materials not bound to any specific learning module.

E-learning can be a solution for students that are working alongside studies or live in another city and for communities in rural areas (Boulos et al., 2006; Muthuprasad et al., 2021). E-learning offers students to dictate the pacing and path of their learning experience which can be effective in reducing redundant information but requires self-discipline (Muthuprasad et al., 2021; Zhang et al., 2004). Early research on e-learning found it more effective than traditional, instructor-centered classroom teaching (Zhang et al., 2004).

Adopting e-learning can be difficult. In the mid-2000s online learning content, especially video and audio formats, had the issue of having sufficient bandwidth for download (Boulos et al., 2006; Zhang et al., 2004). Even today variations in internet connectivity impose challenges in implementing e-learning, especially in countries with bigger digital divides (Almendingen et al., 2021; Muthuprasad et al., 2021; Valencia-Arias et al., 2019; Zalat et al., 2021). Different levels of knowledge and skills of technology affect the efficiency of learning online as some educators and learners might find using online learning systems uncomfortable (Hsia et al., 2014; Muthuprasad et al., 2021; Ong et al., 2004; Valencia-Arias et al., 2019; Zalat et al., 2021). Lack of immediate feedback and answers to questions has been found to affect e-learning experiences negatively (Muthuprasad et al., 2021). Even if learners find e-learning effective, they can still prefer traditional classroom teaching as learning is a socio-cognitive activity (Almendingen et al., 2021; Zhang et al., 2004). Issues of intellectual property, copyrights, and security are often overlooked when implementing e-learning materials. They add more workload for educators but are vital for sustainable learning modules (Boulos et al., 2006; Zhang et al., 2004). Vandalism, authenticity, and false information should be considered when developing and consuming e-learning materials. Ensuring that students can verify the origins of information and allowing student feedback for errors and invalid information is vital for a safe and secure learning environment. In addition, the threat of security issues affects perceived credibility and might lessen acceptance of e-learning systems (Boulos et al., 2006; Ong et al., 2004; Zhang et al., 2004).

Conventionally e-learning materials have been static, meaning they do not have any moving parts or interaction (Taylor & Pountney, 2009; Zhao et al., 2020). Many approaches to transforming static materials and utilizing the many possibilities of digital learning materials have been proposed. A combination of wikis, blogs, and podcasts can be used as mind tools, secondary sources of learning for reflection and amplification of new information, to connect with peers, and to apply variation to learning (Boulos et al., 2006). In specific situations, dynamic tools like animation can help with schema acquisition when used and developed appropriately (Taylor et al., 2007, 2008; Taylor & Pountney, 2009). Static contents have been sometimes found to be more effective than dynamic materials as they impose less cognitive load and help focus on the material while dynamic learning environments might include more redundant content (Huang & Fang, 2023).

2.2.2 Decorative images and learning materials

Multimedia learning is learning from words (written or spoken) and graphics (informative or decorative) (Kozma, 1991; Mayer & Moreno, 1998). Mayer and Moreno's cognitive theory of multimedia learning claims that presenting information in words and pictures instead of just words is more effective for learning as visual and verbal materials are processed in different systems (Mayer & Moreno, 2002).

The effects of illustrative images on learning have been studied in varied contexts. There are multiple interpretations of the effect (Burin ym., 2021; Cardwell ym., 2017; Jaeger & Wiley, 2014; Lenzner ym., 2013, 2013; Mikheeva ym., 2021; Rey, 2012; Schneider ym., 2016; Wiley, 2019). Some studies suggest that illustrative images disrupt learning (Burin et al., 2021; Jaeger & Wiley, 2014) and create a false sense of competence (Cardwell et al., 2017; Wiley, 2019), some state that illustrations generate positive experiences and motivation (Carney & Levin, 2002; Lenzner et al., 2013), others argue that decorative images also help to acquire knowledge (Mikheeva et al., 2021; Schneider et al., 2016). Schneider et al. (2016) concluded that decorative images in learning materials can be classified into two categories. Conducive decorative pictures have a positive effect on learning and seductive decorative pictures impair learning.

The effect illustrative images have on learning computer programming has not been studied before. The problems with teaching programming lie in the learning material. Cheah (2020) researched in their literary review reasons for difficulties in programming learning and teaching. One cause observed was the use of static materials, such as books, hand-outs, and presentation slides. The problem with static materials is their generic contents and lack of dynamic elements. Learning materials should adjust to the learner's needs and represent the dynamic structure of software. The review highlighted that students struggle especially with understanding abstract features, creating algorithms, problem solving, and logical thinking. Conventional teaching methods unsuitable particularly for teaching object-oriented programming and creating mental representations of problems were common problems found in research (Cheah, 2020).

2.3 Cognitive load theory in e-learning materials

Understanding cognitive load theory and the effects that create cognitive load for learners is vital for creating usable learning materials. However CLT-based design principles can make the design process more efficient and ensure all aspects imposing cognitive load are examined. In this chapter, guidelines for instructional material design that utilize cognitive load theory are presented and summarized. Similar principles are combined to create an extensive list of design suggestions to follow when developing learning materials that aim to manage the cognitive load of learners and promote learning. First, the included studies are presented briefly after which the principles are summarized and given examples of use in TABLE 1.

Mayer & Moreno (2003) provide nine principles for reducing cognitive load in multimedia learning. They give five examples of problems that could occur with multimedia learning and provide one or two solutions for each. Their principles are based on the idea that visual and verbal information is processed in different channels and that cognitive load is imposed by three kinds of demands essential processing, incidental processing, and representational holding. If one channel is overloaded with incoming information it can be off-loaded by reassigning some information to the other channel or by restructuring the material. Eliminating or managing the three different kinds of processing is used also. For the split-attention effect, Mayer and Moreno have three solutions off-loading, aligning, and synchronizing**.** Off-loading is the reassigning of information from one channel to the other. Aligning encourages placing text next to corresponding graphics. Synchronizing is when mutually dependent materials are presented simultaneously instead of successively. The redundancy effect is solved by eliminating multiple duplications of essential information. Innately complex material can be helped by segmenting and pretraining. Segmenting allows learners to process given information before continuing. Pretraining should teach important elements before the actual learning situation so that later learners can focus on the relationships of the elements. Individualizing can also help by making sure learners get materials suitable for them and that they have the right tools for holding mental representations. Seductive details, or interesting but irrelevant elements, can take up cognitive capacity and prevent learning. They should be either eliminated by weeding or ignored by signaling important information from the material to learners with cues and signals.

Morrison & Anglin (2005) summarized cognitive load theory design heuristics for e-learning from the special issue of Educational Technology Research and Development. The articles in the issue were also discussed by van Merriënboer & Ayres (2005). Morrison and Anglin recognized nine principles that could be used to develop good learning materials from the perspective of CLT. They emphasize that the heuristics should be used with care before extensive research is done to validate them. The first heuristic tackles high-element interactivity experienced by learners with a low level of technical knowledge. Initial learning of technology skills before actual learning enhances their performance. Van Merriënboer and Ayres remind in their summary that sequencing of pretraining for the learning platform and actual learning content can however be detrimental for learners with a higher prior knowledge of the technology. Morrison and Anglin's next heuristic regards task design. Exploratory practice that allows learners to consider different options in a realistic context involves experienced students more in the learning process than worked examples do. However, more novice students will not benefit from exploratory practice like experienced students. One heuristic suggests that representations including both verbal and visual nonredundant information results in better performance compared to providing the information only through verbal or visual means. The next heuristics cover supporting schema acquisition. Learning should be promoted by stimulating the learner by involving them in the process of understanding. This could be done by encouraging learners to analyze their own performance before giving feedback or correct answers. Furthermore, for learners with a lower level of prior knowledge, learning processes should be explicitly induced while higher expertise learners can benefit simply from elements that facilitate mental processes. A study on annotations generated three heuristics. Verbal annotations in a text can improve learning. Utilizing one type of annotation, such as definitions or explanations, doesn't necessarily induce extraneous load but enhances germane load. However, using multiple types of annotations in a learning material results in lower performance.

Cook (2006) provides seven design considerations for visual representations used in science instruction. Many of the principles concern elements only possible to implement in e-learning and the rest can be applied to digital learning environments. The split-attention effect is addressed here by suggesting that multiple representations should be linked in time and space so that information doesn't need to be integrated from multiple sources. Like others, Cook also highlights that providing information in two different presentations, or in dual-mode presentations, increases mental capacity. Morrison and Anglin referred to this as using two nonredundant representations while Mayer and Moreno called it off-loading. Furthermore, Cook suggests that when combined with a visual element, verbal information should be provided as narration instead of written text, to give more attention to the visualizations. Animations can be effective learning tools when designed properly. Too fast and complex videos require too much cognitive effort to enable learning. For novice learners, highly interactive elements should be isolated from each other to prevent unintentional simultaneous processing. Once again guidance in schema acquisition, that is implicitly evoking learning processes, can help understanding. Especially for more experienced learners, eliminating redundant information is important for avoiding using mental effort multiple times for the same information.

Mayer (2017) highlights 11 research-based principles for creating multimedia instruction. The principles are based on the multimedia principle that students perform better when they learn with words and pictures rather than words alone. Mayer divided the principles into three categories, five to extraneous load, three to intrinsic load, and three to germane load. The principles concerning the reduction of extraneous load are coherence, which is to exclude extraneous material, signaling, which is highlighting essential material, redundancy, which is to not add on-screen text to narrated graphics, spatial contiguity, which is to place words next to corresponding graphics, and temporal contiguity, which is to present corresponding narration and graphics simultaneously. All but the first one are self-explanatory and have appeared also in the principles presented before. Coherence by reducing extraneous material in Mayer's article is explained as limiting seductive details that are interesting but irrelevant elements such as fun tidbits or relaxing background music. The three principles for managing intrinsic load are segmenting which is presenting multimedia lessons in user-paced segments, pretraining which is teaching the key terms before a multimedia lesson, and modality which is presenting words in spoken form rather than printed text. Once again we can see the recurrence of principals from previously presented guidelines. The last three principles foster germane load. Though similar to other guidelines, personalization is approached from a new perspective here. In multimedia learning, it is beneficial to present words in a conversational style rather than a formal style. Other principles for germane load are voice which is to use a human voice rather than a machine-like voice and embodiment which is to use human-like gestures and movement for onscreen agents.

Principle	Description	Example	Sources
Multimedia	Use both verbal and visual information, instead of only one of them.	Learning material about spider webs has an animation depicting the process of creating one and text explaining its physical properties.	(Cook, 2006; Mayer & Moreno, 2003; Morrison & Anglin, 2005)
Aligned	Place text next to corresponding visualizations.	In a map of Europe, the countries' names are placed within the countries instead of having a list next to the map and connecting the list and map with lines.	(Mayer, 2017; Mayer & Moreno, 2003)
Synchronized	Present mutually dependent materials simultaneously.	A new term is explained with an in-text annotation, e.g. a lead, instead of using footnotes.	(Cook, 2006; Mayer, 2017; Mayer & Moreno, 2003; Morrison & Anglin, 2005)
Reduced	Remove redundant or duplicated information regardless of their presentation.	Learning material with an animation explaining photosynthesis does not explain the process again in the text.	(Cook, 2006; Mayer, 2017; Mayer & Moreno, 2003)
Segmented	Provide the material in a way that allows learners to pace their learning sessions as they wish.	An animation showing the stroke order of a Chinese character can be paused at any point.	(Mayer, 2017; Mayer & Moreno, 2003)
Pretrained	Teach essential elements of the learning platform and key terms of the topic before beginning actual learning.	Before the first lesson, students can complete a tutorial on how code is run on a programming learning website.	(Mayer, 2017; Mayer & Moreno, 2003; Morrison & Anglin, 2005)
Personalized	Ensure learners have learning materials suitable for their prior knowledge and abilities.	A driving school’s online learning material is adapted based on the student's previous license.	(Cook, 2006; Mayer, 2017; Mayer & Moreno, 2003; Morrison & Anglin, 2005)
Guided	Guide learners to use schema acquisition tools and induce cognitive processes.	Students have to analyze their performance before revealing correct answers or giving feedback.	(Cook, 2006; Mayer & Moreno, 2003; Morrison & Anglin, 2005)
Focused	Weed out seductive details and signal important information.	Learning material about felines has all species with bold text and excludes a funny gif of Garfield.	(Cook, 2006; Mayer, 2017; Mayer & Moreno, 2003; Morrison & Anglin, 2005)
Narrated	Use narration instead of written text with visualizations.	Video about how lightning is produced is explained simultaneously with narration instead of subtitles.	(Cook, 2006; Mayer, 2017)
Humanized	Make on-screen agents, narrations, and texts human-like.	A video about AI is narrated with a human voice and uses casual language.	(Mayer, 2017)

TABLE 1 CLT-based principles for designing e-learning materials.

3 RESEARCH AND METHODS

Studying the effects instructional materials’ components have on learners’ cognitive load is vital for developing learning experiences that promote learning. However, restructuring or redesigning existing materials can be time-consuming and expensive. Educational institutions might not have the resources to invest in instructional design and professors' time is already very limited (Ylijoki, 2013). It should be tested if some quick and easy alterations to learning materials could be effective in promoting learning. One of these methods could be adding illustrative images among the textual learning materials. Free images are easy to find and use. They could provide a quick fix for sprucing up existing text-based instructions and promote students’ motivation and willingness to read provided materials. However, studying the effects decorative images have on the cognitive load of learners should be done to ensure the possibly redundant elements do not hinder learning.

3.1 Research question and hypothesis

The research question is do illustrative images affect the cognitive load of learning computer programming? From the research questions the following hypotheses are induced:

H_0) Learning material’s illustrative images do not affect the cognitive load of learning computer programming.
H_1) Learning material’s illustrative images affect the cognitive load of learning computer programming.

Additional hypotheses are tested:
H_2) The smaller the perceived cognitive load of the *learning material*, the better the success in tasks is.
H_3) The smaller the perceived cognitive load of the *tasks*, the better the success in tasks is.

3.2 Participants

Participants were recruited through the University of Jyväskylä's faculties' email lists and through personal social media accounts on Instagram, Facebook, and LinkedIn. For email, the invitation letter was written on the email itself. For social media platforms, a link to a website containing the invitation letter was included. The invitation advertised that participants could win a 30 € gift card to Finnkino-movie theaters. The emails for the lottery were collected through a different question form which could be accessed through a link after completing the study.

Participants were divided into two groups based on the parity of their birthdays. People born on an even day were instructed to open one link, while people born on an odd day were to open another one. The method of using birthday parity for dividing groups was thought to produce more even groups and be more anonymous than for example dividing by the first letter of the participant's last name. The method however did not produce similar-sized groups as the odd-day group got more replies. Dividing with the birthday-parity method should be considered carefully, especially when expecting a smaller sample size.

The required sample size for a statistically significant result from two independent samples' mean comparison with t-tests was calculated with G*Power. The calculation was done as two-tailed with effect size d = 1.0, alpha risk α = 0.05, power $1\text{-}\beta$ = 0.8, and equal sample sizes. The result was a sample size of 34, or 17 per group. There have been multiple studies where Paas' (1992) 9-point scale resulted in an effect size over 1.5 (Chien & Chang, 2012; Khacharem et al., 2013; van Leeuwen & Rummel, 2022; van Meeuwen et al., 2014; Van Merriënboer et al., 2002), which applied to the power analysis could allow a total sample size of 18 or 9 per group.

The recruitment period for 34 participants was planned to last for three weeks but was extended to four in hopes of acquiring more participants. However, only a total of 28 answers were received of which 16 were for the no images group (odd birthday) and 12 for the images group (even birthday). Participants whose self-evaluated level of programming was under 3, who had never used or tried Python before, and who did not know what the term class means in object-oriented programming were accepted. Two answers did not fulfill these requirements for a novice Python programmer and were excluded to eliminate possible expertise reversal effects. Overall number of subjects shrank to 26 with both groups losing one participant. All data analyzed going forward will not include these two cases.

The no images group had 15 participants with one under 18-year-old, four 18–25-year-olds, eight 26–35-year-olds, and one both in the 46-55 and the 56-65 age groups. The images group had four participants in the 18-25 age group, two 26–35-year-olds, three 36–45-year-olds, and again one in both the 46-55 and the 56-65 age groups. Neither group had any participants over 65 (see FIGURE 1).

Having multiple questions establishing the participants' knowledge of programming was found useful in understanding their actual level of prior knowledge. Some participants seemed to underestimate their level of knowledge on a Likert scale. Two participants in the no images group self-evaluated themselves to have little knowledge (2 on a scale of 1 to 5, none to excellent) in programming. All other participants (11 in the images group and 13 in the no images group) did not have any self-evaluated competence in programming. However, in both groups, only 9 participants reported not having learned or tried programming anywhere before. In the no images group four had tried programming in higher education, one in comprehensive school and one had self-studied it. In the images group one had tried programming in higher education and one at work. 10 people in the no images group had not tried any programming languages before, two had tried C#, one Python, one R, and one participant reported having tried "some language in middle school". For the images group nine people had not tried any programming languages, one participant had tried C++, one C#, and one JavaScript. None of the participants had used Python before. One participant had reported having seen or read the language but not tried it themselves. No one reported knowing what the term class means in object-oriented programming. See Appendix 3 for all participant statistics.

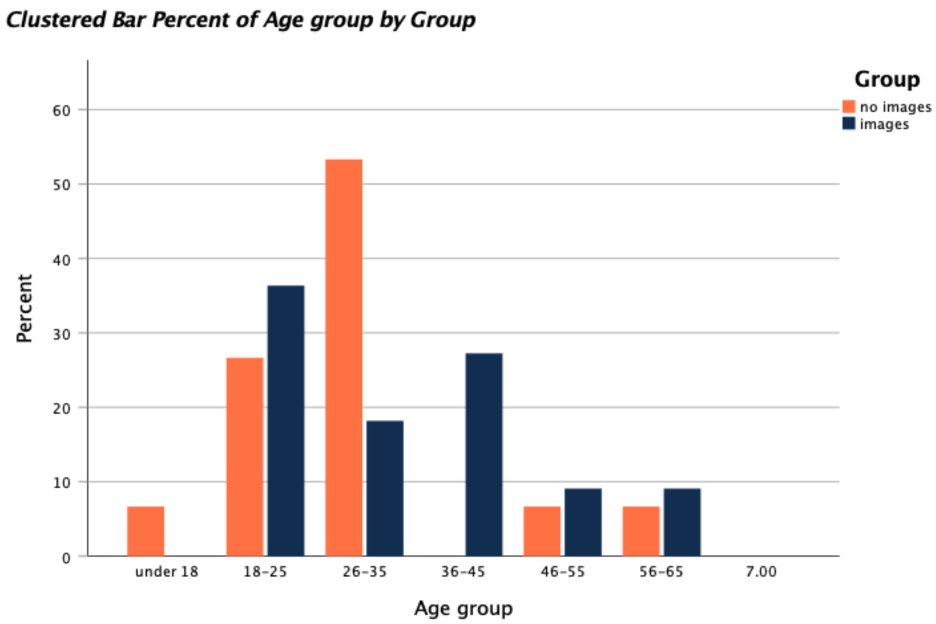

FIGURE 1 Distribution of age categories for both groups is uneven and centers around 18–35-year-olds.

3.3 Learning material

The learning material was specifically developed for the study. Python was chosen for the examples as it allows to present rather complex topics for novice learners with comparatively simple syntax. The material was a static website made with HTML and CSS-styling and hosted on the University of Jyväskylä's users.jyu.fi-server. The study was designed to be done with a tablet or computer. To make sure participants used an appropriate device, the material was hidden with an overlay and error message when opened with a screen too small (see Appendix 2 for demonstration). Illustrative images for the images group website were sourced from pexels.com which provides free, modifiable images without the need to credit the creator (Free Stock Photo & Video License - Pexels, retrieved 4/2023).

The learning material design attempts to minimize all other cognitive loads so that the cognitive load imposed by the existence of illustrative images could be observed. The images were placed on the left side of the page to reduce the split-attention effect by placing multiple representations in close approximate. The images affect the line breaks of the text, so for the no images website, the text width was set to follow the images website. The material also tries to mimic conventional designs of other online programming materials such as using code blocks and text styling every time actual code is shown.

The learning material (see Appendix 2) taught the basic concept of classes. The topic was chosen for its important role in object-oriented languages and its relative complexity. The material would impose some cognitive load on novice learners but would also allow some acquisition of knowledge. It was designed so that readers would be able to at least read and recognize class and object structures written in Python and get used to the syntax of the language. The overall length was kept short to make sure that participants would read the whole material through. The material was divided into four sections 1) Objects and classes, which introduces the basic concept of classes and objects, 2) Implementing classes in Python, which provides a worked example of a class called Friend, 3) Creating objects in Python, with a worked example of creating an object emma using the Friend-class and some print-commands, 4) Complete program, that gives a standalone example of one class, creating objects with it and printing some text for the user to see.

The decorative images for the images group's learning material were chosen instinctively from the stock photo database. The goal was to choose images that had some relation to the example it was attached next to and that had a positive impression. All images can be seen on the screenshot in Appendix 2.

The material was tested on two test subjects. Emphasizing code blocks with grey backgrounds and linking the examples to real-life use cases were redesigns due to feedback from test subjects. The intrinsic nature of the material was not tested further. More comprehensive tests might have revealed that the material was too complex and vague for novice learners which were mentioned in multiple participant feedbacks. If extensive testing is not possible, pre-existing learning materials that have been proven usable could be used instead of custom-made materials.

3.4 Procedure

3.4.1 Study phase

After answering the background questionnaire, which results were discussed on page 21 Participants, the participants were provided with a link to the learning material and instructed to study it thoroughly. They were informed that the learning material nor any other material shouldn't be used in the following tasks. On the top and bottom of the learning material website, the participants were reminded to close the material after studying it. On returning to the questionnaire they answered the cognitive load scale from Morrison et al. (2014) to evaluate the cognitive load of the learning material. The cognitive load questionnaire was followed by an optional text box for comments about the material.

3.4.2 Tasks

After studying the learning material either with or without images and evaluating its cognitive load, participants completed four tasks. It was emphasized that the tasks should be done without any outside sources like the learning material or third-party online materials. The tasks were placed on individual pages of the questionnaire, but participants could return to previous tasks. One subject confessed in the open text feedback that they did go back to find answers from previous tasks. It can be deduced that also other participants utilized previous tasks and found answers from the phrasings of the questions. If no outside sources should be used while answering, future research should ensure that flipping between the tasks is not possible.

The task page included the task itself, a three-item cognitive load scale modified from Morrison et al. (2014), Paas' cognitive load scale (1992), and an optional open feedback textbox. Task 1 was a multiple-choice question asking to identify what the presented structure was called. Task 2 asked the participant to write a Song-class that gets the attributes song, performer, and release year. Task 3 asked the participant to create an object named finland with the Country-class provided in the question. Task 4 was a multiple-choice question that provided a class, one object, and two print functions and asked what is printed to the user.

Tasks 2 and 3 were producing tasks that required the participants to write actual code to the Webropol survey's text box. The written code could not be run and so testing was not possible. Also, the text boxes did not allow using the tab button for indentations, so participants were instructed and taught to use spaces instead of tabs. It was reminded on the tasks' 2 and 3 questions that spaces should be used instead of using the tab button.

All tasks were scored by the same evaluator so no biases should occur in assessments. The multiple-choice questions were scored 1 if correct and 0 if incorrect. For task 2 each completely correct line of code was worth 1 point and a correct idea with some syntax errors could be awarded half a point. No recognizable idea of the correct concept for that line was scored 0. The example answer in FIGURE 2 would be scored a total of three points. The maximum score for task 2 was 5. For task 3 one point was granted for the correct naming of the object, correct instantiation of the class, and correct use of three arguments (see FIGURE 3).

Task 2 example

Answer	Points
`Class: Song`	.5
`  def __init__(self, name, performer, published):`	1
`    self.name: “Rick Astley”`	.5
`    self.performer: “Never Gonna Give You Up”`	.5
`    self.year: “1987”`	.5

FIGURE 2 Example of answer and scoring for task 2.

Task 3 example

Answer	`finland =`	`Country`	`(finland,`	`euro,`	`5,6m)`
Points	1	1	.5	.5	.5

FIGURE 3 Example of answer and scoring for task 3.

3.5 Results

3.5.1 Data analysis

To assess the null hypothesis H_0) *Learning material's illustrative images do not affect the cognitive load of learning computer programming*, images and no images groups' cognitive load scores were compared. The mean of the four tasks' cognitive load scores was calculated individually for both scales, Morrison et al. and Paas. The learning material's cognitive load score was tested for intrinsic, extraneous, and germane parts as well as a whole. The overall cognitive load score from the learning material's three first items and the modified Morrisons et al. scale of the tasks were combined to analyze the whole learning experience's intrinsic cognitive load. Analyzed cognitive loads and their descriptive statistics can be seen in TABLE 2. The mental cognitive load across all cognitive load measures was more desirable for the images group than for the no images group. Germane load should be increased to promote learning and for the images group germane load of the learning material was higher (no images: M = 5.9, images: M = 6.6). All other scores of cognitive loads, the scores that should be reduced for enhancing learning, were lower for the images group.

Descriptive and non-parametric test statistics					
		Descriptive statistics		**Mann-Whitney U**	
		Group: no images n = 15	Group: images n = 11		
Learning material cognitive load, mean of all items (1-10) from Morrison et al. (2014)	*M*	5.7	5.5		
	Median	5.7	5.2	*U*	73.0
	SD	.83	1.34	*p*	.646
	SEM	.21	.40		
Learning material cognitive load, mean of intrinsic items (1-3) from Morrison et al. (2014)	*M*	6.1	5.4		
	Median	7.3	3.7	*U*	72.5
	SD	3.00	2.50	*p*	.610
	SEM	.78	.75		
Learning material cognitive load, mean of extraneous items (4-6) from Morrison et al. (2014)	*M*	5.0	4.0		
	Median	5.0	3.7	*U*	67.0
	SD	3.01	2.23	*p*	.443
	SEM	.78	.67		
Learning material cognitive load, mean of germane items (7-10) from Morrison et al. (2014)	*M*	5.9	6.6		
	Median	6.3	7.0	*U*	94.0
	SD	3.10	2.91	*p*	.574
	SEM	.80	.88		
Mean intrinsic cognitive load of all tasks (Morrison et al., 2014)	*M*	6.2	4.8		
	Median	7.4	4.6	*U*	53.0
	SD	2.49	2.00	*p*	.134
	SEM	.64	.60		
Mean cognitive load of all tasks (Paas, 1992)	*M*	5.4	4.7		
	Median	5.8	5.0	*U*	62.0
	SD	1.81	1.50	*p*	.305
	SEM	.48	.45		
Mean intrinsic cognitive load of learning material and tasks (Morrison et al., 2014)	*M*	6.1	5.1		
	Median	6.3	5.2	*U*	64.0
	SD	2.66	1.97	*p*	.357
	SEM	.69	.60		
Mental efficiency (Paas & Van Merrienboer, 1993)	*M*	1.0	1.0		
	Median	.9	.9	*U*	77.5
	SD	.62	.87	*p*	.799
	SEM	.16	.26		

TABLE 2 Descriptive and Mann-Whitney U statistics show no significant differences between the images and no images groups.

The statistical significance of the differences in cognitive loads was tested. Non-parametric tests were used as the sample sizes of both groups were small and not equal. An Independent-Samples Mann-Whitney U Test was performed to evaluate whether the perceived cognitive load of the learning material and tasks differed between the no images and images groups. The results (see TABLE 2) indicated that the distribution of cognitive load is the same for both no images and images groups for all cognitive load categories. Based on the results the null hypothesis remains true and the alternative hypothesis H_1) *Learning material's illustrative images affect the cognitive load of learning computer programming* is dismissed.

Hypothesis H_2) *The smaller the perceived cognitive load of the learning material, the better the success in tasks* was tested with the learning material's cognitive load score and the tasks' combined points. The correlation was analyzed with a scatterplot and a nonparametric correlation test Spearman's rank correlation coefficient. The scatterplot (see FIGURE 4) suggested that there is no evident correlation which was reinforced by the Spearman's test (r_s = .06 and p = .757)

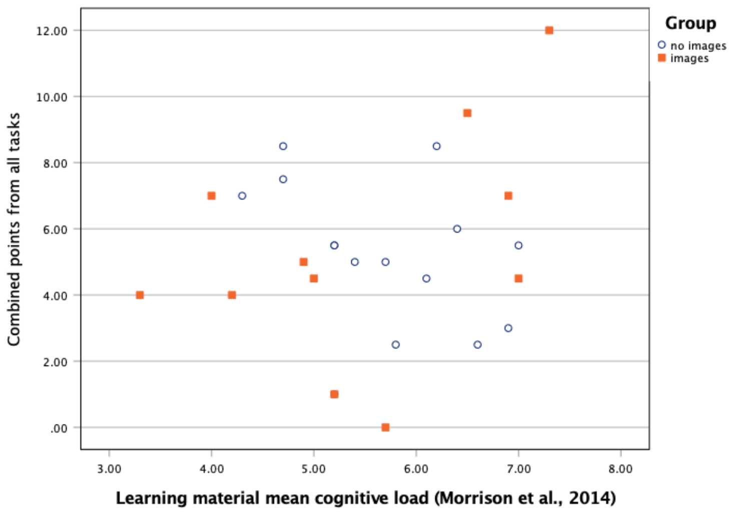

FIGURE 4 No correlation was found for task success and learning material cognitive load.

hence hypothesis H_2 is rejected.

Hypothesis H_3) *The smaller the perceived cognitive load of the tasks, the better the success in tasks* was tested from two perspectives of Morrison et al. and Paas cognitive load scales. Both scatterplots (see FIGURE 5 and FIGURE 6) show a weak correlation between cognitive load and task success. Spearman's test resulted in r_s = -.48 and p = .013 for Morrison et al. scale and r_s = -.46 and p = .019 for Paas' scale. Both results indicate a medium to large negative correlation between the task scores and cognitive load, that is when cognitive load decreases the task success increases. The same hypothesis was tested also on the overall intrinsic cognitive load of the learning experience. The scatterplot (see FIGURE 7) and Spearman's test (r_s = -.50, p = .011) both indicated a medium to large correlation. Hypothesis H_3 is accepted. Correlation statistics can be seen in TABLE 3.

Mental efficiency (Paas & Van Merriënboer, 1993), was analyzed for the tasks. Performance was defined as the percentage of points from all tasks. That is, 12 points would make the performance 100%. The mental effort was defined as the mean cognitive load from the tasks' Paas scale readings. Performance (P) and effort (R) were transformed into z scores and used to calculate mental efficiency (E) with the formula $E = \frac{|R-P|}{\sqrt{2}}$. For both groups, the mean mental efficiency was calculated as $M = 1.0$. An Independent-Samples Mann-Whitney U Test found no statistically significant difference between the mean mental efficiencies ($U = 77.5$, $p = .799$). See TABLE 2 for all descriptive statistics.

FIGURE 5 Negative correlation was found for task success and cognitive load score with the Morrison et al. scale.

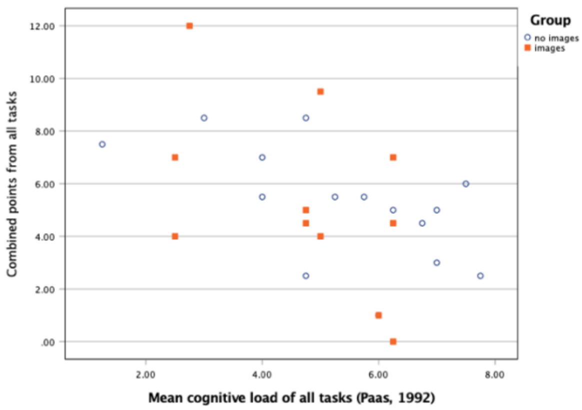

FIGURE 6 Negative correlation was for loa found task success and cognitive d score with the Paas scale.

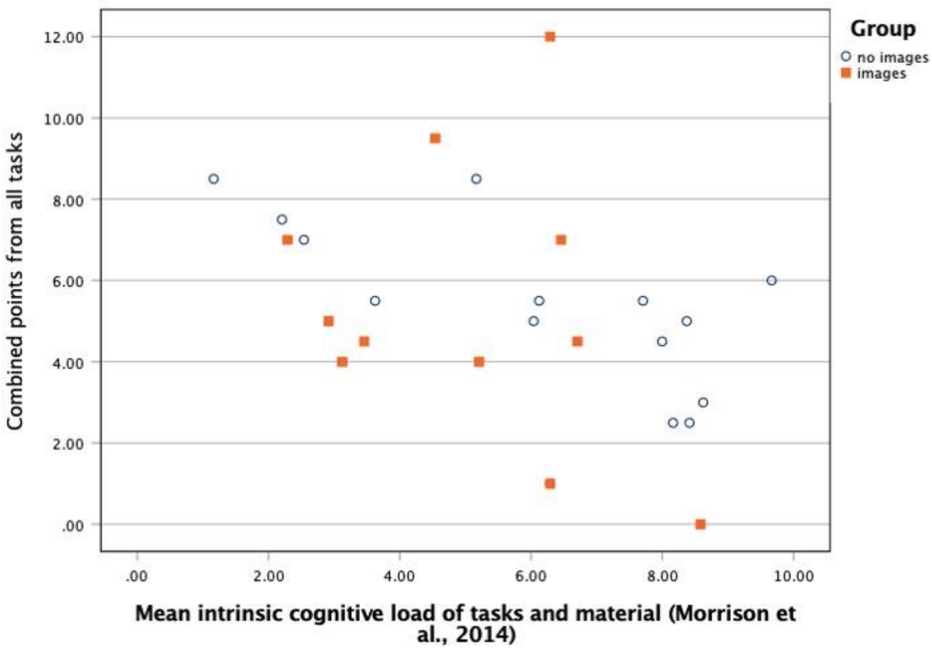

FIGURE 7 Negative correlation was found for task success and combined cognitive load of learning material and tasks.

Spearman's rank correlation coefficient		
Cognitive load category	Combined points from all tasks	
	r_s	p
Learning material mean cognitive load (Morrison et al., 2014)	.06	.757
Mean cognitive load of all tasks (Morrison et al., 2014)	-.48	.013
Mean cognitive load of all tasks (Paas, 1992)	-.46	.019
Mean intrinsic cognitive load of tasks and material (Morrison et al., 2014)	-.50	.011

TABLE 3 Correlation statistics for task points and different cognitive load categories show a significant correlation between task points and task cognitive load, and task points and intrinsic cognitive load.

3.5.2 Decorative images' effect on cognitive load

The results of the study suggest that decorative, context-specific images placed alongside computer programming material in a static e-learning environment do not affect perceived cognitive load significantly. There were however insignificant differences that might be able to be validated with a bigger sample size.

In the optional feedback boxes, both groups commented about having difficulties with the material, especially when it came to learning new terms. Having to learn several new terms and understanding their meaning for the code was too a complex task for many. Also, the definitions and explanations for the terms were considered lacking for novice learners. The impact the images had on the material's cognitive load might have been overpowered by the high cognitive load imposed by the unnecessarily complex topic and insufficient definitions.

In general, the material's examples were commended by both groups for being clear visually and contextually and having practical topics. One participant from the no images group said that the learning material was "a little boring and textbook-ish". The visual look of the material was commented on by participants from the images group to be clear and the pictures were considered nice. As no comments on the structure or visuals came from the no images group, it could be suggested that visually more diverse materials make a bigger impact on learners. The implications this effect has on learning should be studied further.

It was found that the smaller the tasks' cognitive load was the better participants performed. This supports cognitive load theory that implies that managing cognitive load can support learning and performance. Many participants commented that the tasks themselves weren't complex but were mentally difficult because they had difficulty recollecting the material. On the other hand, some participants commented that the task wasn't difficult since the learning material stuck to their minds quite well. It seems like the difficulty of the task is not as important as the learner's ability to complete it. Participants who had a difficult time remembering the needed concept commented feeling annoyed and discouraged. This could support the idea of using goal-free problems that promote using the knowledge learner has instead of forcing them to try and recollect something they haven't acquired yet. However, no previous studies about using goal-free problems in learning programming were found. Another solution to avoid frustration when learning programming could be to not introduce producing problems too early. This would require somehow assessing the acquired knowledge without too complex tasks.

Still, improving static materials with decorative images does not seem to support learning and research should be done on how static materials could be redesigned efficiently and resourcefully to be dynamic and interactive.

4 CONCLUSIONS

Cognitive load is the mental workload humans need to carry out tasks. Cognitive load theory (CLT) was developed to create instructional materials that aim to minimize the required cognitive load. CLT divides the cognitive load imposed by learning materials into three categories of intrinsic, extraneous, and germane. Intrinsic cognitive load is created by the problem's innate complexity and is commonly managed by different methods of sequencing the learning material. Extraneous cognitive load is imposed by the learning material's design and structure. Many methods of reducing extraneous load have been developed, many of which aim to reduce redundant information. Germane cognitive load is the effort required for schema acquisition. It can be induced by managing extraneous load or coaching learners on how to construct schemata.

Educators' understanding and implementation of cognitive load theory in instructional design can be beneficial for creating effective learning experiences. Many instructional models have been created to ease the development of learning materials. They should be taken into consideration especially as e-learning has made usable learning materials even more important. Variations in technology knowledge within teachers and students and educators' resources are an issue when it comes to developing or implementing new materials. It should be studied what are effective and resourceful ways of doing instructional material redesign.

This paper studied if decorative images could help with cognitive load experienced during computer programming learning. Decorative images have been found to create a more positive learning experience and make students more motivated to learn. There has been contradicting research on if decorative images actually promote learning. Learning material images have been studied at least in the contexts of statistics and natural sciences learning. No previous studies on illustrative images' effects in the context of programming learning were found.

The study was conducted by creating a learning material about Python's classes and objects and having one group study it without images and one group with context-specific decorative images. The material was designed for novice learners but was later found through participant feedback to be too complex for beginners. After studying the material participants evaluated the cognitive load it imposed. They continued to complete four tasks related to Python's classes and objects and evaluated the cognitive load each task imposed.

The group who studied the learning material with decorative images experienced slightly less cognitive load compared to the group that studied text-only material. However, the difference was not statistically significant. The relatively high cognitive load of the plain material itself could have affected the results. If all mental effort was allocated to understanding the text and examples no capacity was left for the images to catch the learner's interest or be utilized for schema acquisition. More extensive research with more suitable learning material and bigger sample size could provide more significant results.

The correlation between task performance and cognitive load was assessed. It was found that the smaller the cognitive load was the better task performance was. This demonstrates that perceived cognitive load can be used to predict task success in computer programming learning. Thus cognitive load theory could be adopted by those designing programming learning materials to ensure good and effective learning experiences. This could be following instructional design principles based on cognitive load theory, like those presented in TABLE 1, or paying attention to the cognitive load perceived by users throughout the learning experience with systematically placed cognitive load measures like Paas' (1992) or Morrison et al. (2014). Instructional designers, would that be experts in that specific area or professors and other educators, should recognize the insights cognitive load theory gives about learning experiences and how to manage them accordingly. Cognitive load measurements are easy to implement, especially for e-learning materials. They can be analyzed quickly for understanding how changes in a learning material affect its effectiveness and learnability.

In addition to educators, learners themselves could benefit from understanding the effects cognitive load has on learning. Some participant feedbacks in this study emphasized the importance of cognitive load theory and found it interesting to evaluate their own cognitive load during the study. Recognizing the important relationship between task performance and perceived cognitive load could make it easier for learners to manage their learning paths and schedules. Many use e-learning computer programming materials found free online and having the skills to recognize good materials from bad ones is vital. Not only the content itself, but the presentation of it is important for learning. Minimizing split-attention and redundancy effects during the learning experience can be done by knowledgeable learners themselves. Paying attention to the cognitive load experienced and adjusting study sessions accordingly could be an effective way for learners to manage their learning. Instructional design could also benefit from learners who have some knowledge about CLT and can give feedback from that perspective. Further studies on how learners' prior knowledge of CLT affect performance and cognitive load should be done.

The study has some problems when it comes to validity and reliability. The reported results should not be referenced as evidence for decorative images' effect on learning programming or for the main result of cognitive load's effect on task performance. The validity of the study is discussed further here.

First, the external validity is examined. As the study was done completely remotely, the time and place the participants answered the questionnaire could not be controlled. Busy surroundings and quiet environments might affect the results individuals produce. However, in real-life e-learning, the time and space of learning varies also. It could be suggested that in e-learning studies these aspects should not be controlled to ensure realistic and applicable results. This study did not collect any information about where and when the learning happened so correlations between it and cognitive load could not be analyzed. Also, beyond prohibiting the use of small vertical screens, the technology used was not questioned. Furthermore, the used web browser could affect the experience. One participant commented that on task 4 one of the options had an odd line break. The problem however couldn't be recreated. The background questions of the participants focused on evaluating their programming knowledge. The only question not related to programming background was age group. There was no correlation found between age group and performance or perceived cognitive load. Most participants fell between the ages of 18-35 and different results might be possible with a majority of younger or older participants. Educational background nor intelligence was recorded as they were considered unnecessary for the study. People using and studying programming, especially from e-learning materials can be from all age groups, backgrounds, and abilities so the design of learning materials should take into consideration all demographics. Gender, which is often asked in research, wasn't recorded either. Lindqvist et al. (2021) emphasize that researchers should consider carefully when asking about gender in their studies and look at gender from four aspects: physiological aspects, self-defined gender identity, legal gender, and gender expression. As this study did not aim to analyze the effects these aspects of gender have on learning programming and cognitive load, it was deemed unnecessary to include gender in the background questions. In conclusion, the time and place of the learning environment were not controlled and hence could be generalized outside the study as e-learning is not bound to any specific environments. However, small screens were not allowed, which doesn't correspond to real-life usage of e-learning materials, and participants' background checks were not comprehensive enough to determine generalizability. Therefore, the study's external validity is not strong.

Secondly, the study's internal validity is considered. The problem of Paas' scale's validity was attempted to be avoided by adding another, possibly more reliable cognitive load scale. However, the complete Morrison et al. scale did not find significant results to analyze. For the tasks' the scale was modified by presenting only the first three items. The reliability of the modified scale was not studied. The modified scale resulted in a slightly bigger correlation between cognitive load and performance than Paas' scale. Even though multiple previous studies have argued for the validity of Paas' scale and used the Morrison et al. scale successfully, the validity of the used scales remains questionable. The tasks were scored by the same person which minimizes the possibility of inconsistencies with evaluation but does not remove it completely. As the scoring of each line or element was either 1 point, half a point, or no points, the results were not very precise, and seemingly very different answers could have scored similar points. Since both the cognitive load scores and task performance have problems with validity the internal validity of the results is weakened. The finding that perceived cognitive load could predict task performance has been observed in previous studies which could provide support for the validity of the main result of this study.

The learning material was not sufficiently tested. The pictures for the images group learning material were chosen instinctually and based on giving the viewer a positive feeling. The affective effect of the images was not tested, and they could impose different emotions on different people and so create different cognitive loads. Also, the results could be different with different individual images. The sample size of the material was too small to report any true results. For the learning material's cognitive load score, the probability of falsely retaining the null hypothesis (Type II error) was 77% (calculated with G*Power). Also, it should be noted that the sample sizes were notably unequal.

It can be concluded that decorative images do not affect the cognitive load of learning computer programming, but some evidence correlation between cognitive load and task performance was found. Managing the cognitive load of programming materials by other means than adding illustrative images should be researched further and implemented to promote learning.

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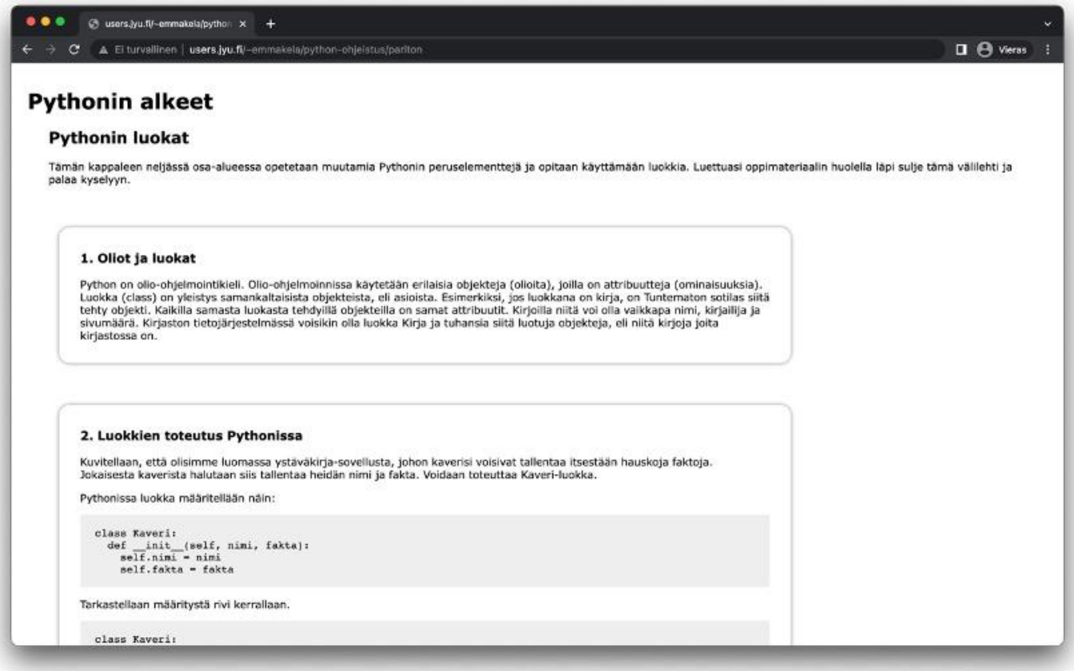
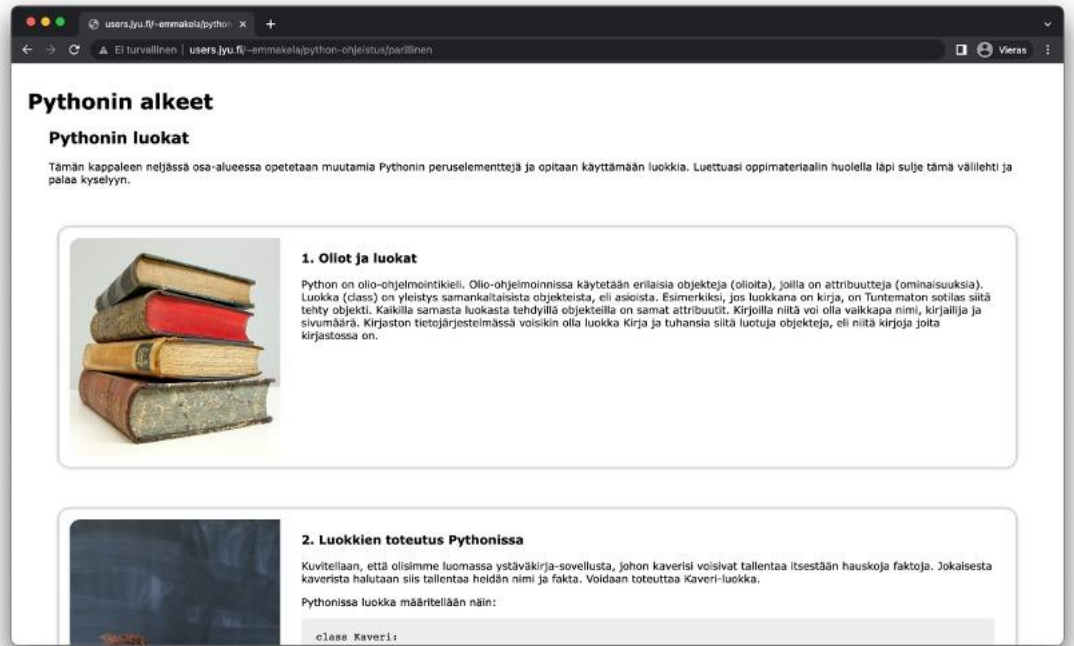
APPENDIX 1: SCREENSHOTS OF THE LEARNING MATERIAL

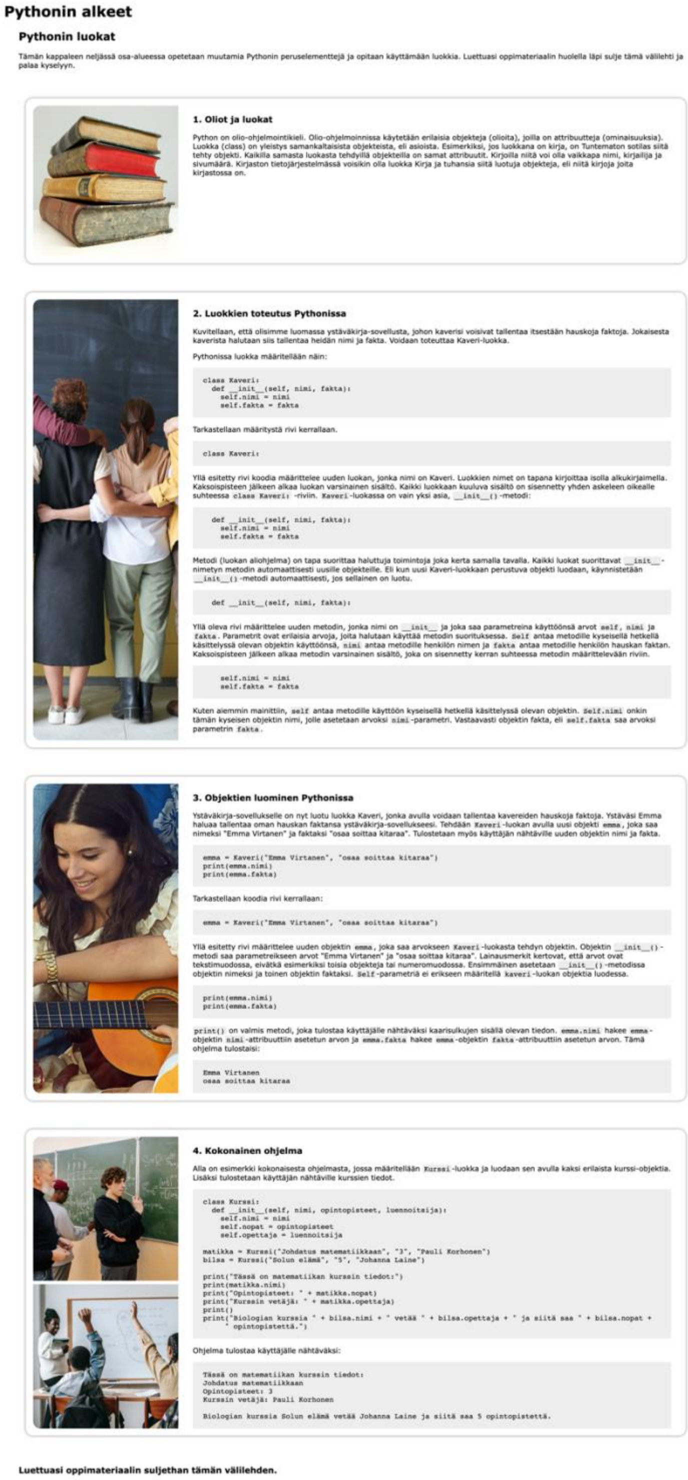


Screenshot of the no images learning material



Screen shot of the images learning material.

APPENDIX 2: FULL CONTENT OF THE MATERIAL AND SMALL SCREEN ERROR



Screenshot of the images group's learning material. To see how the material fitted on a horizontal screen see Appendix 1.

Screenshot of the error message shown for small screens

APPENDIX 3: BACKGROUND STATISTICS

Background questions (single choice)

Question	Option	Frequency (percent)	
		Group: no images (n = 15)	Group: images (n = 11)
Age	under 18	1(6.7)	0 (0)
	18-25	4 (26.7)	4 (36.4)
	26-35	8 (53.3)	2 (18.2)
	36-45	0 (0)	3 (27.3)
	46-55	1 (6.7)	1 (9.1)
	56-65	1 (6.7)	1 (9.1)
	over 66	0	0
Level of programming competence (1- none, 5 - excellent)	1	13 (86.7)	11 (100.0)
	2	2 (13.3)	0 (0)
	3	0 (0)	0 (0)
	4	0 (0)	0 (0)
	5	0 (0)	0 (0)
		15 (100.0)	11 (100.0)

Experience on Python background questions (single choice)

Question	Option	Frequency (percent)	
		Group: no images (n = 15)	Group: images (n = 11)
Experience of Python	No experience.	14 (93.3)	11 (100.0)
	I have seen or read Python, but not used.	1 (6.7)	0 (0)
	I have used Python a couple of times.	0 (0)	0 (0)
	I use Python at least once a month.	0 (0)	0 (0)
	I use Python weekly	0 (0)	0 (0)
I know what class means in object-oriented programming	Yes	0 (0)	0 (0)
	No	15 (100.0)	11 (100.0)
		15 (100.0)	11 (100.0)

Programming background questions (multiple choice)			
		Frequency (percent)	
Question	Option	Group: no images (n = 15)	Group: images (n = 11)
Where have you learned or tried programming?	No programming experience.	9 (60.0)	9 (81.8)
	Comprehensive school	1 (6.7)	0 (0)
	Higher education	4 (26.7)	1 (9.1)
	Online course not related to studies.	0 (0)	0 (0)
	At work	0 (0)	1 (9.1)
	Self-study	1 (6.7)	0 (0)
	elsewhere, where?	0 (0)	0 (0)
What programming languages have you tried?	None	10 (66.7)	9 (81.8)
	C	0 (0)	0 (0)
	C++	0 (0)	1 (9.1)
	C#	2 (13.3)	1 (9.1)
	Haskell	0 (0)	0 (0)
	Java	0 (0)	0 (0)
	JavaScript	0 (0)	1 (9.1)
	PHP	0 (0)	0 (0)
	Python	1 (6.7)	0 (0)
	R	1 (6.7)	0 (0)
	Rust	0 (0)	0 (0)
	Swift	0 (0)	0 (0)
	Other, what/which?	1 (6.7)	0 (0)
		15 (100.0)	11 (100.0)