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"Knowledge transfer during e-learning: the impact of learners' characteristics and support activities on learning outcomes"

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Yulia Chervyakova

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1. Introduction

Organizational learning is critical for the success of the organization. It allows the organization to quickly adapt to the changing environment and be successful in the long-term perspective (Olivera and Argote, 1999). Organizational learning builds on a past knowledge and experience, it "occurs through the shared insights, knowledge, and mental models of separate of members of the company", though is not equal to the sum of individual learnings, but rather "is influenced by a much broader set of social, political, and structural variables" (Marquardt 2002p. 43). According to Senge (1990) organizational learning is possible only through learning individuals. Even if individual learning is in place, it still does not guarantee organizational learning. On the other side, without individual learning no organizational learning is possible.

Among the different ways of individual learning available, I will narrow my research to so called e-learning, what generally means any kind of applying electronic technologies aimed at creating learning experience, and even more precisely – to the self-paced standalone courses, requiring no interaction with a trainer or colleagues (Horton, 2011).

The interest to this learning method grew even before the pandemics with 90 per cent of corporations using e-learning already by 2015 (KPMG, 2015). The research of mid-pandemic years concluded that "the increasing number of COVID-19 cases requires distance learning and encourages its rapid growth" (Suzianti and Paramadini, 2021, p.1). Nowadays above 75% of all of organizations intend to organize digital development or delivery of at least 40 % of all their trainings (Deloitte, 2021). It is expected that the global e-learning market will increase from USD 200 billion in 2019 to USD 375 billion in 2026 (Global Market Insights, 2021).

Knowing the growing importance of this learning method, the scholars all over the world are looking into the factors, which influence the knowledge transfer, happening during the online learning. Some of them (McEnrue, 1989; Colquitt, LePine and Noe, 2000; Hopkins, 2016) argue that the individual characteristics of learners, like their demographics, cognitive ability, cultural factors, self-efficacy, motivation, play an important role in overcoming learning-related stress and thus affect the self-efficacy of learners and the learning outcomes.

A lot of effort is made to find out, what can be done to improve the learning outcomes of digital learning. A number of authors (Nelson, 1990; Wong, 2007; Sawang, Newton and Jamieson, 2013; Sivankalai, 2021) conclude that providing support to learners before or during the learning process, allows the learners to come to better results.

In this work I look deeper into if and how exactly both the learners' characteristics and the availability of the support to learners influence the learning outcomes and if it is really the case. I suggest that supporting activities help to reduce the negative influence of certain learners' characteristics on the individual learning outcomes, measured by the results of knowledge assessments right after conducting the training.

Among the learners' characteristics in the focus of my thesis there are the age of learners, their language competency and their digital proficiency. This selection is made based on the preliminary analysis of the literature and the expert opinions of HR professionals. Most importantly is that the data related to these individual characteristics can be easily found in the HR systems of the companies, and thus the results of my work could be easily applied in business.

As a next step I investigate the types of support in more detail and test, which of the support types is the most suitable for the learners with certain individual characteristics. Differentiating the types of support, I separate them based on the digital or face-to face method as well as on the individual or group support.

Thus, the main focus on this master's thesis is on the effectiveness of certain ways of delivering stand-along e-learning courses to adult learners with different individual characteristics. In particular, I investigate the importance and effect of additional activities, supporting learners in passing e-learning modules

Eventually, my goal is to contribute to creating the effective digital learning strategy of the organization, to assure effective implementation of this particular way of learning and investigate how it depends on the learners' characteristics and on the method of delivery.

Specifically, the aim of this study is to determine the link between the individual characteristics of learners, method of digital learning delivery and learning outcomes. This thesis aims at answering the following research question:

Do the learners' characteristics and support activities influence individual learning outcomes during e-learning?

There are two steps in my research, aimed at achieving this objective. The first step is a literature overview to determine the factors, influencing the knowledge transfer during the digital learning. In the second step, it is empirically tested what is the link between the individual characteristics of learners, method of digital learning delivery and learning outcomes.

This master's thesis is structured in the following way:

Chapter 2 reviews the relevant literature and the research made in the field of knowledge transfer, models and mechanisms of knowledge transfer, learning outcomes, digital learning support of the digital learning and concept of e-learning and blended learning, the connection of learners' characteristics to individual learning outcomes. The goal of this chapter is to identify the research gap and formulate the hypotheses.

Chapter 3 describes the research methodology and the research design. In particular, the insights to the data collection process and operationalization of dependent, independent and control variables are provided. This overview enables the selection of a suitable statistical approach to testing the formulated hypotheses.

Chapter 4 presents the results of the data analysis made with the help of R software.

Chapter 5 provides a summary of the findings. In includes the questions for discussion and describes limitations of the work, as well as theoretical and managerial implicaitons.

2. Literature Review

In this section I provide a theoretical overview of the main literature streams dealing with the transfer of knowledge within the organization, the factors influencing the quality of knowledge transfer and importance of the characteristics of learners and the channel of knowledge transfer for its efficiency. I narrow down the discussion about the channel to the topic of digital learning and evaluation of its efficiency.

First, I would like to point out the literature related to the organizational learning, knowledge creation and transfer process within the multinational company, highlighted in the set of articles by Kogut and Zander, (1993), Nonaka (1994; 2005) Szulanski (1996), Prusak and Davenport (1998), Olivera and Argote (1999) and the others. Knowledge is described as a combination of data and processes within the organization, created by their members' work and interaction with each other, which results in the beneficial experience (Olivera and Argote, 1999). Though describing the processes of creation, retaining and transferring of knowledge within the organization, these scholars relate both to the planned and unintentional knowledge transfer, created as spillovers of daily operations of the multinational firm.

My research is aimed rather at the investigation of "intentional" effort of digital training courses on the learners. Thus, in my literature review I also touch upon the articles, dealing with educational aspects characterizing digital learning in general and e-learning in particular. These sources describe the research rather in the field of education than of business, but are still relevant for my study. And finally, I refer to some later articles, dealing with the company induced digital learning of adult employees in the organizations, which are at the nearest to the aim of my work.

2.1. The Concept of Knowledge Transfer

2.1.1. Definition of Knowledge and Knowledge Transfer

This thesis is focused on certain methods of organizational learning. As per Olivera and Argote (1999, p. 1124) "organizational learning is a change in the knowledge that occurs as the organization acquires experience". Knowledge transfer is mentioned in this study as one of the subprocesses of organizational learning, along with the knowledge creation and retention. First of all, I would like to discuss the nature of the knowledge and knowledge transfer.

Howells (2002) defines knowledge as a dynamic framework or structure, which enables the storage, processing and understanding of the information. Nonaka (1994) argues that knowledge is a multifaceted concept and not just static information, but a dynamic human process of justifying personal beliefs as part of truth-seeking.

Polanyi (1966) first formulated a famous distinction between explicit and tacit knowledge. Explicit knowledge can easily be formulated, documented and shared. Successful implementation and use of explicit knowledge depend on its correct evaluation and accessibility to those who plan to use it in order to assure sustainable advantage for the organizations (Prusak and Davenport, 1998).

Tacit knowledge on the other hand can hardly be articulated expressed and effectively transferred. Sometimes this type of knowledge is associated with learning without awareness, a process referred to by Polanyi (1966) as "subception".

Moving from the definition of individual knowledge to organizational knowledge, one can mention that the new knowledge within the organization is created as a result of the interaction of explicit and tacit knowledge. In this aspect the organization provides a certain context in which tacit and explicit knowledge stay in touch with the external economic conditions and are embedded into the daily operations (Nonaka, 1994).

Knowledge nowadays is considered to be the main resource used in performing the work in organizations (Marquardt, 2002). The author argues that "knowledge has become more important for organizations than financial resources, market position, technology, or any other company asset" (p. 13).

Olivera and Argote (1999) discuss the connection between the knowledge within separate organizational units and learning. They argue that in case of learning happening within one and the same organizational unit, it can be seen as knowledge creation, whereas when the knowledge is developed from the experience of another unit, this process can be identified as knowledge transfer.

Indeed, for multinational company it is crucially important not only to create, but also to effectively transfer the knowledge across borders (Kogut and Zander, 1993). Companies, which are not aware of their knowledge components and don't have efficient knowledge transfer processes cannot be successful, "because knowledge assets are difficult to buy in a market" (Prusak and Davenport, 1998, p. 89).

Szulanski (1996, p. 28) defines knowledge transfer as an "exchanges of organizational knowledge between a source and a recipient unit in which the identity of the recipient matters".

Autio and Laamanen (1995) were the first to describe the mechanism of organizational knowledge transfer. They refer to it as to a specific form of interaction between two or more social entities during which technology or knowledge is transferred. When this process between the parties takes place continuously, one can speak about the "flow" or the "channel". The transfer process depends on the nature and characteristics of knowledge transfer object, of the "channels" and "mechanisms", by which one can provide an efficient knowledge transfer and on contextual factors of this process (Battistella, De Toni and Pillon, 2016).

According to Prusak and Davenport (1998) the goal of knowledge transfer is to increase the value of an organization by improving its ability to perform certain work. They argue that knowledge is being transferred spontaneously in the organization on an everyday basis. Though the strategies to knowledge transfer allow to encourage it and make it more efficient. Tacit knowledge is specifically hard to get transferred from the source where it is created to other parts of the organization. Multinational companies often use international rotation and exchange programs to facilitate this transfer.

2.1.2. Models of Knowledge Transfer

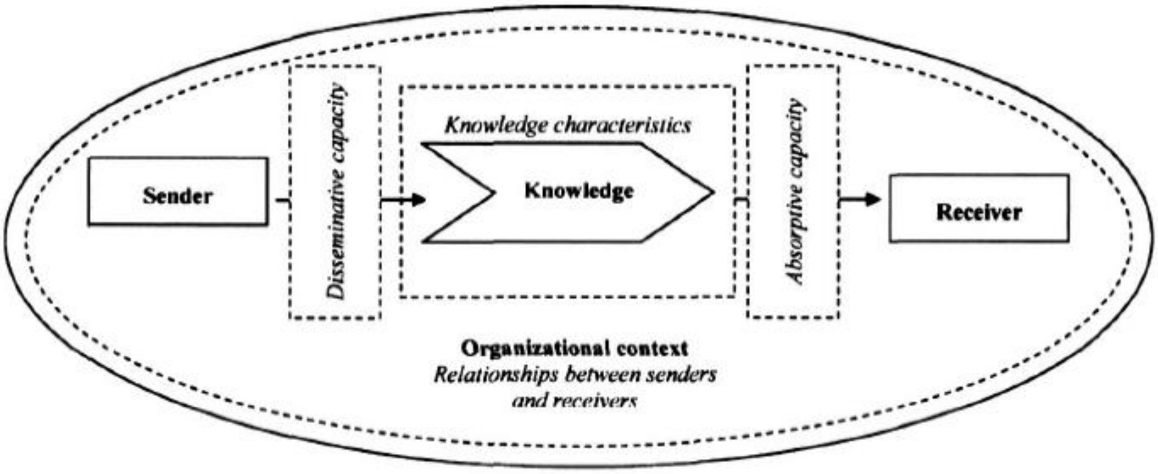
Different scholars created and described the models of knowledge transfer and discussed, what contributes to the efficiency of this process.

Prusak and Davenport (1998) describe two major processes of the knowledge transfer. These are transmission, or presenting knowledge to a potential recipient, and absorption by that person or a group.

Transfer could take place only if the knowledge is absorbed, rather than simply made available to the recipient.

Szulanski (2003) mentions that the effectiveness of the transfer depends to some extent on the disposition and ability of the source and recipient, on the strength of the tie between them and on the characteristics of the object of knowledge. One of the models published by Minbaeva (2007) can be seen on the Figure 1.

FIGURE 1: KNOWLEDGE TRANSFER: A SCHEMATIC DIAGRAM (MINBAEVA, 2007)



In Bold – elements of knowledge transfer

In Italics – barriers/determinants associated with the four elements of knowledge transfer

According to the model by Minbaeva (2007) presented in the Figure 1, the main elements, describing the knowledge transfer are: sender and receiver of knowledge, transferred message (knowledge) and organizational context. The author also mentions barriers, associated with the knowledge transfer process, such as characteristics of knowledge, characteristics of senders (disseminative capacity), characteristics of knowledge receivers, especially absorptive capacity, and the characteristics of the sender-receiver relationship.

Related to the knowledge characteristics, presented on the model (Fig. 1), the tacitness of knowledge or the ability to articulate the knowledge before transferring it, is mentioned by Minbaeva (2007) to be the most important. Kogut and Zander (1993) also refer to the „codifiability“ of knowledge as vital factor for assuring the knowledge transfer. The authors argue that the degree of knowledge articulation even influence the speed of capability transfer. They also mentioned another knowledge characteristic, important for the organizational knowledge transfer – a system dependence, or the degree of hierarchical or functional integration of a certain knowledge withing multinational organization. The piece of functional knowledge (production or marketing know-how), which is separated from the complex organizational structures, is claimed to be easier to transfer.

According to Minbaeva (2007), success of the knowledge transfer depends rather on the characteristics of the individuals involved in the transfer process and on the context in which this transfer occurs, than on the characteristics of the knowledge itself.

Disseminated capacity, referred to on Fig. 1, is related to the characteristics of knowledge senders. For example, in the work of Szulanski (1996) a possible lack of motivation to share knowledge from the side of a source is highlighted as the first characteristic of a sender. According to the author, the source could also be perceived as unreliable, which would also negatively affect the transfer process. Minbaeva (2007) suggests that the decision to transfer knowledge is driven by such behavioral characteristics of senders as the ability and the willingness to share knowledge.

Nevertheless, the recipients' characteristics, specifically their absorptive capacity, are considered in research to be even more meaningful in the process of knowledge transfer than the senders' characteristics (Szulanski, 1996). Empirical research by Szulanski (1996), Olivera and Argote (1999) and the others shows that absorptive capacity plays an important role in knowledge transfer, organizational learning and firm innovation processes.

According to Cohen and Levinthal (1990) the absorptive capacity can be defined as the ability to recognize the value of new external information, assimilate it, and apply it for commercial purposes. This term was widely used in research with respect to multinational companies as a factor, relating the performance of the international firm and its competitive advantage to the firm's ability to learn from diverse environments within which they operate (Song and Shin, 2008; Minbaeva *et al.*, 2014). In the work of Minbaeva *et al.* (2014), the authors relate different aspects of absorptive capacity to the employees' individual features – ability and motivation.

First being formulated on the organizational level, the definition of absorptive capacity is now widely used in in the research of individual learning as one of important learner's characteristics. For example, in the recent study of the data from 648 respondents working in a multinational corporation Yildiz *et al.* (2019) investigate individual-level absorptive capacity, based on a person's motivation, ability and opportunity, and confirm that intrinsic motivation of a person and his/her overall ability are the key antecedents of absorptive capacity, which can increase in case of international assignments of an employee to distant countries.

Some of the scholars agree that the quality of knowledge transfer within a learning process also depends on the good match between its design and the characteristics of the parties (Holton, 1996; Hopkins, 2016).

Thus, the past research allows us to percept a link from the macro-level characteristic of a firm, assuring the effective organizational knowledge transfer, organizational learning, innovation activity and competitive advantage of a company, to the micro-level absorptive capacity of an individual.

For the purposes of my research the micro-level individual characteristics of employees or learners have special interest. In the separate chapter of this work, I would like to pay more attention to the learners' characteristics and their relation to the learning and learning outcomes, described in the literature, focused mostly on educational topics.

2.1.3. Channels and Mechanisms of Knowledge Transfer

Effective channel of transfer helps to overcome barriers to knowledge transfer, described above, and bridge the technical and communication gaps between sender and receiver or learner. Autio and Laamanen (1995) describe a stable flow of knowledge, which turns to the connection or a mechanism between the sender and receiver and name it a "channel".

In his “broadcasting model” Malik (2002) discusses the diffusion of knowledge as a part of intra-firm technology, knowledge transfer process and the types of communication channels used. He refers to the “mode of transfer” block in his model, containing the mechanisms of this transfer, such as movement of people, know-how, information in the form of manuals and reports, IT hardware, software, equipment, tools, etc.

Battistella, De Toni and Pillon (2016) highlight the channels and mechanisms of knowledge transfer as an important dimension of knowledge transfer analysis. In particular, they differentiate the process mechanisms or the modes of organization and services, and output mechanisms or search results. All in all, the knowledge transfer is facilitated by employees’ rotation, as well as by technology development, and the development of individuals (receivers), for instance, through training activities (Olivera and Argote, 1999).

Finally, Minbaeva *et al.* (2014) concludes that the key element in knowledge transfer is not the original knowledge, but is more likely to be the level to which the receiver acquires the knowledge, which can be useful, and applies this knowledge in their own work and thus builds the link between the quality of knowledge transfer and the properties of organization-receiver.

Prusak and Davenport (1998) argue that while transferring knowledge from the global to local organization local definitions may express something, which is considered to be a truth on the local level only, but then can get lost when moving towards a global standard. They mention the “inherent tension” between local and global stakeholders, existing in any codification process, and the value of making the knowledge comprehensible to a variety of people. Thus, knowledge transfer methods should be attended to in the context of organizational and national culture.

Among the cultural factors that inhibit knowledge transfer Prusak and Davenport (1998) mention the lack of trust, different cultures, languages, prejudices related to specific “ownership” of knowledge by particular groups, “not invented-here” syndrome.

2.2. Learning and Its Types

Learning is defined by (Marquardt, 2002) as a process of gaining new knowledge by individuals, which results in their changed behavior. The areas, identified by the author are cognitive (intellectual), affective (emotional), and psychomotor (physical). In his book “Building the Learning Organization” the author argues that learning is a continuous process and it is built into the daily work of the employees and has strategical importance for the organization. He also refers to the learning as to a “social phenomenon”, while “ability to learn and the nature of our knowledge are determined by the quality and openness of our relationships” (p. 51).

Senge (1990, p. 191) highlights that the learning is rather active than a passive process. He argues that, “learning is about building the capability to create that which you previously couldn’t create. It’s ultimately related to action, which information is not”.

Speaking about classification of learning Marquardt (2002) describes that not only the already existing information is processed during the learning, but also new solutions to newly realized questions are created. Learning process is a continuous phenomenon and does not necessary requires a teacher or even a structured training activity. It is rather a personal, group, and organizational ability. Along with that, a training is defined only as one of the methods of the broader learning process, which is imposed (pushed) on a learner, whereas learning is a continuous process, where learner is internally motivated.

Consequently, the learning is divided in levels: individual, team or group, and organizational. Among individual learning opportunities the following learning types are identified: self-managed learning, learning from coworkers, computer-assisted learning, daily work experiences, special assignments on projects, and personal reflection. Team learning is opposed to a simple team training and identified as creating knowledge by processing complex problems, taking innovative action, and solving problems collectively within the team. Organizational learning is seen by the author as more than just the sum of individual and team learning, but rather as a "result of the knowhow of the whole organization working in unison" (Marquardt 2002, p. 43).

For any contemporary organization it is vital to learn faster in order to be able to adapt to changes in the environment and assure the competitive position of an organization. Learning that occurs throughout the organization offers organizations the best opportunity of not only surviving but succeeding (Marquardt, 2002).

For the definition of organizational learning, I'd like to refer to Giannakos, Mikalef and Pappas (2022), who argue that organizational learning process by all means includes the knowledge sharing. It enables opportunities for growth at the individual, group, team, and organizational levels. Thus, organizational learning and knowledge transfer are linked.

Peter Senge (1990, p.3) even defined a special term "learning organizations" to underline the importance of creating a special learning environment in the organizations, "where people continually expand their capacity to create the results they truly desire, where new and expansive patterns of thinking are nurtured, where collective aspiration is set free, and where people are continually learning to see the whole together".

Nevertheless, it goes without saying that organizations can develop only with the help of learning employees. And only the trained and empowered employees can assure the existence of learning process on organizational level (Senge, 1990). The purpose of the learning organization can be defined as the foundation of professional development, the ongoing growth of human capital with which companies drive more innovation, higher levels of service, and financial results. Organizations worldwide require that learning is delivered with greater speed, at less cost, and more effectively to workplaces and mobile workforces that are affected more dramatically than ever by daily changes in the marketplace (Marquardt, 2002).

In order to keep up with the increasingly competitive environment, organizations are forced to operate under the conditions of intense information and knowledge exchange. Traditional learning approaches often fail to meet the always increasing demands. According to Giannakos, Mikalef and Pappas, (2022, p. 662), there is a great need of up-to-date learning methods and mechanisms with the learner-centered approach. The authors mention such methods as smart learning, social learning, experimental learning and the necessity to include them into more traditional learning settings. Modern learning should be "just in time, just what's needed, and just where it's needed" (Marquardt, 2002, p.5).

The authors highlight the following advantages of the digital technologies in learning process: available as needed and just in time, increased the quality, relevance, and speed of learning, allowing control by a learner, geographical and time flexibility, consistency and efficient delivery across the organization, adjustment to individual learning styles, ability to update continuously, availability of both push and pull approaches and cost-efficiency (Giannakos, Mikalef and Pappas, 2022).

There certainly is a need for flexible, efficient life-long learning. To address this need, modern learning systems and training methods can be applied, among important factors there are easy and intuitive design, high learner satisfaction, and integration into the business processes of organizations. Under the condition of constant change of competencies, required from workers in the organizations nowadays, it is important to apply agile competency models and ways of working (Giannakos, Mikalef and Pappas, 2022).

2.3. Digital Learning as a Method of Knowledge Transfer

2.3.1. Knowledge Codification

One of the variables operationalized in this research relates to the channel or mechanism of the knowledge transfer from source to recipient. Specifically, this is the method of digitalized training. That is why further literature overview deals with the aspect of codification and digitalization of knowledge and digital learning.

Discussing the purpose of the knowledge codification in organizations, Olivera and Argote (1999) mention that simply the learning of separate individuals in the organization is not enough to provide for sufficient organizational learning. They argue that for this purpose the knowledge the individual acquired should be included into so-called "supraindividual repository" to make it easy for usage. As an example of such a repository "a routine or transactive memory system" is mentioned. Thus, the main goal of knowledge codification is to convert the organizational knowledge into a convenient to use form, which is explicit, easy to understand and transfer (Prusak and Davenport, 1998).

Prusak and Davenport (1998) argue that codification in organizations is nothing else as transferring knowledge into the different (and also digital) format to make it accessible and applicable when needed. As an example, they refer to the knowledge or training managers, who can categorize, describe, map and model knowledge and, most importantly, make sure, that knowledge is being effectively used this way. The primary difficulty of this codification process they see in the challenge of knowledge codification, with intact distinctive features and meaningful information. In other words, how to transform knowledge without losing its important properties.

Prusak and Davenport (1998) mention the importance of a narrative for knowledge codification and saving its value:

"Trying to turn knowledge into a 'code' would seem to defeat the purpose of communicating it through resonant storytelling. Once we recognize that narratives are the best way to teach and learn complex 'stuff,' though, we can often encode the stories themselves so as to convey meaning without losing much of its leveragable value" (p.82).

Thus, the scholars agree that in order to transfer the knowledge one has first to codify it.

In the next chapter I would like to speak about recent research devoted to the topic of e-learning as a method of knowledge codification and transferring knowledge within the companies using the modern technology.

2.3.2. Definition of E-learning

The technological progress inevitably changed the way of our communication and learning and also our way of thinking. In its turn it affected even the cognitive abilities of learners and the method of processing information. All that caused the shift of "traditional classroom paradigm" (Garrison and Kanuka, 2004, p. 96).

Thus, shift to digital forms of learning is inevitable in the digitally-driven society. Modern research reveals, how advanced technologies are utilized to enhance organizational learning. It undelines the advantages and limitations of using learning technologies within organizations (Giannakos, Mikalef and Pappas, 2022).

Horton (2011) defines e-learning as "the use of Internet and digital technologies to create experience that educate fellow human beings". According to Wong (2007, p. 56) e-learning is defined as "learning activities that involve computers, networks and multimedia technologies". One more recent definition:

"e-learning refers to an educational concept that utilizes information technology and devices to deliver learning materials and to support distance learning" (Suzianti and Paramadini, 2021, p.1). According to Giannakos, Mikalef and Pappas (2022, p. 629) modern e-learning systems "provide the medium to substantiate the necessary knowledge flow within organizations and to support employees' overall learning".

Servage (2005) sees the major problem of creating straightforward definition of e-learning in the difficulty to define component aspects of e-learning and claims these aspects to be instructional content or learning experiences delivered or enabled by electronic technology. Indeed, all definitions of e-learning broadly encompass the use of computer and internet technology (Sawang, Newton Jamieson, 2013).

Morrison (2003) defines e-learning as continuous assimilation of knowledge and skills by synchronous and asynchronous learning events, which are authored, delivered, engages with, supported and administrated using internet technologies. In his book "*E-learning Strategies: How to Get Implementation and Delivery Right First Time*" the author underlines that e-learning has to stimulate the learner by providing explicit knowledge, but the responsibility to transform the explicit knowledge into tacit stays with the learner themselves. He argues that e-learning delivers process knowledge i.e., it takes subject-matter expertise and applies the process of instructional design to generate a structured training module. He defines the following types of e-learning: live e-learning (virtual classroom), which is synchronous or real time and distributed (asynchronous) e-learning, which can take place "anytime and anywhere" (Morrison, 2003, p. 6). The latter is referred to by Horton (2011) as standalone or self-paced courses. This type of e-learning is in the focus of this thesis.

Horton (2011) describes that both self-paced courses and virtual classroom methods of delivery can be conceptionally used to implement gaming and simulation learning activities as well as for social learning, happening through interactions with the community of experts and peers. Based on the type of used devices the author also separately refers to mobile learning, aided by mobile devices, such as smartphones or tablets, pointing out the importance of this type of learning, which offers learners the highest degree of flexibility.

Elkeles, Phillips and Phillips (2014) highlight the growing importance of blended learning, when, for example a digital self-paced module is combined with the instructor-led session, allowing a higher degree of support and understanding to a learner. Thus, we could differentiate between a stand-along e-learning course and e-learning with a support of the instructor.

E-learning has become a high priority for many companies. In all sectors, both public and private, e-learning is widely used to enable training and development of employees in the workplace, avoid extra travel, promote learners' satisfaction and avoid the costs of large numbers of trainers (Sawang, Newton and Jamieson, 2013, p. 87).

Among the most noticeable advantages of the e-learning method, especially valuable for international corporations, operating in different time zones, the scholars mention time leverage and just-in-time learning opportunity. "E-learning can deliver content anywhere in the world as soon as possible – no other learning channel delivers that" (Morrison, 2003, p. 10). Sivankalai (2021) argues that such elements of e-learning courses as video, moving images and other visuals have a longer-lasting impact on the brain, promote active learning and increase of retraining efficiency compared to the traditional in-class learning. The author states that e-learning programs provide great content variety, can be custom-tailored to the company profile and learner requirements, and that this method is especially effective to apply on-the-job abilities, like internet-searching and generally solve the tasks related to the use of internet resources. He argues that e-learning libraries allow simultaneous access for a large number of learners, with effective access control in place, promote feedback and simplify learning progress evaluation and as well allow access for disabled, representing a step towards inclusion. One more important point mentioned is the possibility of revisiting the course anytime. The author also mentions the growing importance of artificial intelligence in the process of digital learning, which allows to customize education by considering the interest areas of learners, as well as their skills and development needs. According to Strother (2002, p. 13) there is evidence that e-learning in business is a "win-win proposition for all – the learner, the corporation, and the customers".

One must mention special meaning that e-learning acquired during the COVID-19 pandemic era, when many companies tend to replace conventional business as usual with digital solutions, and "e-learning has been proven as effective as the conventional learning process, even better from an efficiency perspective" (Suzianti and Paramadini, 2021, p. 12). In general, the future of e-learning seems bright and dynamic.

There are still some limitations of e-learning mentioned in the literature. For example, Chang *et al.* (2014) mention reduced real interactions and high drop-out rates during the digital training. Wong (2007) argues that self/paced asynchronous e-learning is not suitable for individuals without the self-discipline required to complete all tasks independently. He also refers to the necessity of computer hardware and relevant resources as the factor, preventing the learners to effectively use this training method. The inadequate internet coverage or insufficient bandwidth may hinder the learning process as the downloading of multimedia materials may take a longer time. In their study Suzianti and Paramadini (2021) confirm that the quality of information systems and IT infrastructure have significant impact on e-learning continuance intention.

Among the other challenges connected with e-learning implementation Morrison (2003) mentions sufficient cost of relevant technology, complexity of enterprise-wide implementation and integration of different applications, such as Learning Management System, aimed at managing the learning activities, and most importantly e-learning, within organizations. The investment in the infrastructure for e-learning is expensive and often incurs substantial risks of failure (Mandinach, 2005).

Speaking about e-learning, Morrison (2003, p. xi) mentions that "everyone has learning needs; no one has e-learning needs". The author points out that many executives become bogged down in technological considerations (the how) to the point that the over-riding purpose of an e-learning strategy (the why) is lost. Indeed, being only a tool to effective learning process, e-learning cannot be a goal in itself and depends on the correct implementation in line with learning strategy. And this proper implementation can become a complicated task due to "technology hurdles" and significant change induced across the organization. Hence, a vital role during the e-learning implementation in organizations plays instructional design or a process of translating project goals into the choices of content and technology (Horton, 2011).

2.4. Training Evaluation

2.4.1. Models of Training Evaluation

A well-known four-level approach to a training evaluation was first suggested by Donald Kirkpatrick in 1953, since then has been the most useful framework in the evaluation of training and nowadays is still widely used in research (Falletta, 1998; Drozdova and Guseva, 2017).

Kirkpatrick and Kirkpatrick (2006) mention three main objectives of training evaluation, these are: to justify training costs, to decide whether to continue or discontinue chosen training program, and to gain information on how to improve in future.

According to Kirkpatrick's model, there are four levels of evaluation:

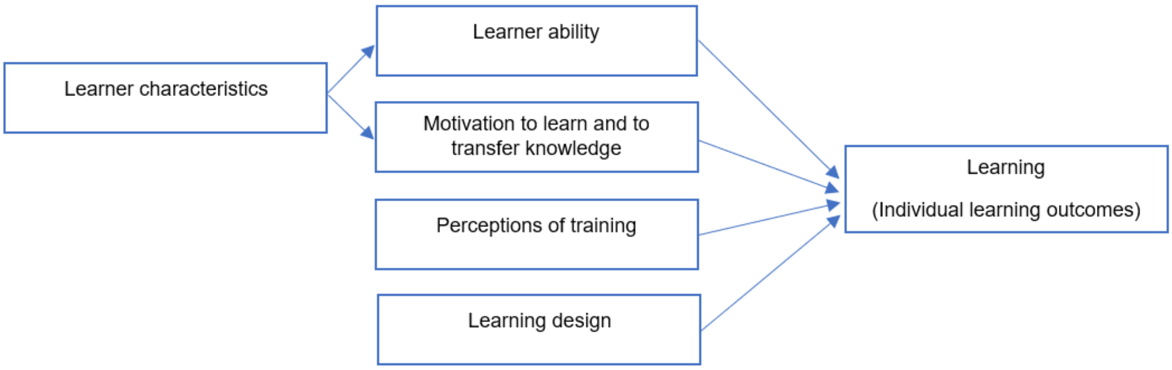
1. reaction or learner satisfaction
2. learning representing "extent to which participants change attitudes, improve knowledge, and/or increase skill as a result of attending the program"
3. behavior or "the extent to which change in behavior has occurred because the participant attended the training program"
4. results for the organization in general (Kirkpatrick and Kirkpatrick, 2006, pp. 21-26).

There is also a fifth level, suggested in the book of Phillips and Phillips (2016) and this is a calculation of a training program cost and return on investment (ROI). Thus, in the following research not the four, but five-level evaluation is often referred to (Drozdova and Guseva, 2017). The ROI aspect turns to be one of the most important in case of learning through technology, as the costs saving in case of transferring instructor-led program into the e-learning module is often advocated as an irrevocable advantage of a digital learning (Elkeles, Phillips and Phillips, 2014).

Nevertheless, a stream of research warns against focusing on the cost impact of the training evaluation. For instance, Morrison (2003) states that ROI proves a poor means of articulating the value of knowledge because knowledge is not quantifiable. He argues against describing corporate training as a purely "vertical e-market place" in which the organization delivers a service to its employees. Servage (2005, p. 309) also warns against treating knowledge as a pure "capital" inside workers' heads. Strother (2002) mentions that decisions about training programs need to be made independently on training cost considerations, and that for this purpose managers need concrete measures of program effectiveness.

Kirkpatrick's model was as well not universally accepted (Falletta, 1998, p. 260). For example, Holton III (1996) argues that Kirkpatrick's model is not a reliable model, but rather a "taxonomy of outcomes". Holton III (1996) suggested his own model with three outcome levels: learning, which influences individual performance, transferring in its turn to the organizational performance. The author argues that this model allows to address the main risk of the Kirkpatrick's model i.e., that "any failure to achieve outcomes from the intervention would be attributed to the intervention itself when it could well be due to the moderating variables" (Holton III, 2005, p. 37). For example, Holton III (1996) underlines the importance of such environmental factor as transfer climate in transferring learning outcomes to on-the-job behavior. For this thesis through it is important to consider the factors, which influence the first level of learning outcomes, defined by Holton III (1996) as "learning", or the level acquired knowledge after the single learning experience, which can be identified as individual learning outcomes. These factors are presented on the Figure 2:

FIGURE 2: THE MODEL OF TRANSFERRING LEARNING TO INDIVIDUAL PERFORMANCE BASED ON THE MODEL BY HOLTON (1996)



The author mentions the importance of individual learners' characteristics, which affect the learner's ability and motivation. For example, motivation to learn is considered to have a direct impact on the learning process (on individual learning outcomes). Among the most important learning characteristics the author mentions conscientiousness (being dependable, hardworking, disciplined, deliberate, and goal oriented), neuroticism (emotional stability), and openness to experience (being interested to learn new things). Learners' perception of training is claimed to be of a limited importance, compared to the Kirkpatrick's model.

The model was updated by Holton III in 2005. In his article Holton III (2005, p. 44) introduces the notion of learning transfer system and defines it as "all factors in the person, training, and organization that influence transfer or learning to job performance" with the transfer climate being a part of it. The author also underlines the importance of peer support, supervisor support and supervisor sanctions for learning transfer.

2.4.2. Evaluation of E-learning

Because of the active development of digital learning method in the last decades, a growing number of research activities are aimed at analyzing information systems in general and e-learning in particular and thus differentiate the assessment approach of digital learning, comparing to traditional one.

Most of them are aimed at measuring user satisfaction of interaction with digital systems, which is a part of (Bailey and Pearson, 1983), and are basically focused on the level one of the Kirkpatrick's model. Al-Fraihat, Joy and Sinclair (2020) in their more recent study point out that though the learner satisfaction is important, it would be better to have it integrated with other approaches to achieve better efficiency in assessing the influence of learner satisfaction on the other learning outcomes. They introduce the more complex model, called Model for E-learning System Success (EESS model), which includes the following elements: technical system quality, information quality, service quality, educational system quality, support system quality, learner quality, and instructor quality. The authors conclude that all these factors are valid and important measures, identifying the e-learning success.

For the purpose of this thesis, the most important is to assess the learning outcomes of such a specific training method as self-paced e-learning modules. In order to do that, scholars use the methods described in the previous section with some relevant adaptations. For instance, in their article Drozdova and Guseva (2017) apply Kirkpatrick's model to evaluate the online training in the banking sector.

Comparing to the other learning methods, e-learning allows to obtain lots of training data. That is why for digital learning it is typical to use quantitative methods for assessing learning outcomes (Mandinach, 2005). The author describes interactive digital test solutions, when the learning items and assessments are automatically administered and adapted based on the trainee's performance during his/her previous learning. It is underlined that there is no one common way of e-learning outcomes evaluation and that the evaluation design should generally depend on a specific setting of e-learning implementation (Mandinach, 2005).

Test scores seem to be the most common way to measure e-learning performance along with the self-assessment questionaries aimed at measuring learner's satisfaction. For example, in the research by Chang *et al.*, (2014) it was concluded the in the group of students who passed electrical machinery class, blended e-learning did not significantly affect students' achievement test scores compared to traditional in-class method, but significantly affected their self-assessment scores.

The overall importance of online assessments in e-learning is summarized by Barbosa and Garcia (2005), who underlines the importance of the evaluating the individual learning outcomes. The benefits of such tests are: identifying the learners knowledge level, evaluating the learner's effort and give them objective feedback, comparing the same learner's progress and the progress of different learners' groups, possibility to continuously adapt and improve the learning setup and creating new learning profiles. Indeed, online assessment tools contribute as a source of feedback to the progress of learners, instructors and instructional designers. Important factor, mentioned by the author, is relative objectivity of such evaluation method or minimizing the "academic dishonesty". The score of online tests is also used in this work as a variable, describing learning outcomes.

However, this level of assessment does not allow either to reveal the long-lasting behavioral change (as per level 3 of Kirkpatrick's model) or to define the organizational impact (level 4). Defining the ROI (level 5) is also out of the scope of this thesis. It can certainly be considered the limitation of this work.

2.4.3. Definition of Learning Outcomes

In order to correctly operationalize learning outcomes, relevant for my thesis, there is a need to make an overview of main research trends in this area. First, I discuss the definition of learning outcomes then analyze the problem of training evaluation approaches in general and in the next chapter specify my research to the methods of assessing digital learning outcomes.

Looking for the definition of learning outcomes one can mention the book of William G. Spady devoted to the concept of Outcome-Based Education who describes learning outcome as "learning results we desire from students that lead to culminating demonstrations" (Spady, 1994, p. 49), i.e. after some period of significant learning experience. The author highlights the importance of the "internal mental process" and of "what the students can do with what they know and understand". The author also refers to the learning outcomes as to the tangible applications of what the student has really learned in the form or real actions or performance.

Adam (2004) as well highlights the importance of the practical application of learning results and thus points at the importance of a written statement, describing what exactly a successful learner is expected to be able to do at the end of the learning course. He aims at avoiding the “confusions between learning outcomes, objectives and aims” (Adam, 2004, p. 19).

On the other hand, learning outcome often has a formal aspect of what is assessed and accredited to learner or a student, and what is celebrated as a student’s achievement. (Allan, 1996).

2.5. Learner’s Characteristics

This chapter will describe the theoretical background of learners’ characteristics, as the set of independent variables in this thesis.

According to the previously mentioned learning evaluation model by Holton (1996), visualized on the Fig. 2, learners’ characteristics play an important role in the transferring knowledge to individual performance of the learners, thus, directly affecting the learning outcomes.

The study of Colquitt, LePine and Noe (2000) reveals the individual characteristics of learners, such as locus of control, conscientiousness, anxiety, age, cognitive ability, self-efficacy, job involvement, to be significant predictors of training motivation and outcomes. Moreover, the authors argue that training motivation plays even more important role in training outcomes than the cognitive ability of learners. They highlight the link between the training motivation and self-efficacy of learners and the importance of the learners’ self-efficacy for the knowledge transfer.

It goes without saying that the special place in scientific research in terms of achieving good learning outcomes is given to the self-efficacy of learners. The term “self-efficacy” was first introduced by Bandura, Freeman and Lightsey (1999, p. 3) referring to a person’s “beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments”. This notion describes how much an individual believes in their ability to do something. A learner must be willing to engage in the training process (Hopkins, 2016).

Self-efficacy in the learning process relates to task effort and persistence in task achievement and is normally transforms into positive training outcomes (Colquitt, LePine and Noe, 2000). A number of researches proved positive relationships between self-efficacy, motivation to learn, and learning outcomes (Martocchio and Webster, 1992). Some scholars mention that self-efficacy can predict learners’ performance in educational contexts even better than actual abilities of individuals (Bandura, Freeman and Lightsey, 1999). This conclusion is important and proves that learners with high self-efficacy better engage in doing a task, therefore they achieve higher score than those learner with low self-efficacy, even though they may have higher ability (Raoofi, Tan and Chan, 2012, p. 61). Thus, the scholars argue that there is a direct link between the self-efficacy of learners and learning outcomes.

The following characteristics of learners are claimed important in research: age, cognitive ability, ability to sufficiently understand the language of the training course, cultural aspect, self-efficacy, motivation (Hopkins, 2016; Horton, 2011). In this thesis the focus is made on the characteristics of age and language competency with respect to learning process in general and digital proficiency which is relevant particularly for e-learning. These variables are of interest for my thesis, because this data is normally available in the organizational HR databases and Learning Management System and thus, the results of this work could be widely applicable for HR departments.

Therefore, the following hypothesis is proposed:

H1: Learners' characteristics influence learning outcomes.

2.5.1. Age of Learners

Although in research the demographic variables were sometimes investigated in the in studies, related to training, most often they have been used as statistical control variables. Only rarely demographic variables were attended to in empirical research. Thus, there is not much theoretical background, connecting demographics to training outcomes (Colquitt, LePine and Noe, 2000).

Nevertheless, as a first step, I would like to present the evidence of the impact of the factor of learners' age for learning process in general and after that I will discuss more in detail about the factor of age in terms of digital training.

The importance of the age perception by both employees and their managers is considered in the study of Cleveland and Shore (1992). They concluded that the age ratings showed a small yet significant relationship to the assessments of developmental opportunities given to employees. It could be connected to the fact that the investing into the development of younger employees could be perceived as more efficient, as they potentially could stay in a company longer than older ones. It was though suggested that while aging, employees and their managers may perceive that the employees' ability and training motivation decrease. Employees' fear of failure prevents older employees from looking for the new training opportunities.

These assumptions are confirmed by the meta-analysis in the study of 256 articles by Colquitt, LePine and Noe (2000), proving that the age of learners is negatively correlated to motivation to learn and post training self-efficacy of learners.

Speaking particularly about the digital type of learning, the literature research reveals the necessity to differentiate the digital learning in the groups of children and adults.

In some studies, referring to undergraduate students, the correlation between the age and the results of learning is shown as follows: students younger than 20 years old show worse learning results in case of digital or blended learning compared to older students (Lim and Morris, 2009). It is logical to suggest that in the groups of children the older ones have advantage, learning digitally.

As argued below, the studies of groups of learners above 20 years old prove the reverse correlation of age and learning results. This thesis is dealing with the employees of international organization. The characteristics of adult learners are not comparable with those of full-time students (Morrison, 2003). That is why it seems important to mention, that I would consider only adult learners in this research.

With regard to such characteristic as the age of adult digital learners, empirical results seem consistent. For example, a field experiment of 68 full-time employees by Martocchio and Webster (1992), who investigated the effects of performance feedback and cognitive spontaneity in human-computer interactions (cognitive playfulness) on microcomputer training performance showed among other findings the evidence of negative correlation between age and learning results. Some other studies have suggested that age is a factor, influencing the balance between so called “crystallized” and “fluid” intelligence: although the learners of higher age could have more job-related information skills and expertise, their ability to engage in the type of reasoning necessary for learning decreased (Horn and Noll, 1994). Data from 98 ethnically heterogeneous employees in the study of McEnrue (1989) indicated that younger employees were more willing to engage in self-development in order to prepare themselves for higher levels of organizational responsibility than were other employees with equivalent managerial career aspirations.

Thus, it would seem that as age increases the ability to learn new skills, especially digitally, decreases, people become less willing to take part in training activities, they find it harder to integrate different sources of information and the amount of time needed to learn increases. With an older target group, it is therefore more important to offer self-paced and well-structured training programs. “Younger people have grown up in a highly technological environment and are often very comfortable with the idea of immediately searching for information as and when they need it, perhaps through YouTube videos, and so may be less dependent on the need for formal learning activities” (Hopkins, 2016, p. 178).

Summarizing these findings, it can be hypothesized that the age of adult learners is negatively related to their learning outcomes.

H1a: The higher age of adult learners negatively affects the learning outcomes of e-learning.

2.5.2. Language Competency

The learner’s ability to sufficiently understand the language of the training course affects learning outcomes and learning experience (Horton, 2011, p.13).

MacIntyre and Gardner (1994) define the language anxiety as the feeling of tension and apprehension specifically in case the language of the training is not a mother tongue. It applies to both speaking, listening, and learning. The authors mention that compared to relaxed students, anxious students artificially limit their actual language knowledge and have more difficulty demonstrating the knowledge that they do possess. Language anxiety is considered to be a situation-specific form of anxiety that is distinct and unrelated to other forms of anxiety (Tallon, 2009). In the study of Gardner, Day and Maclntyre (1992) language anxiety claims a great deal of learner's attention and consume the cognitive and affective resources they would have spent to focus on a task conducted in theirs first language.

The research of language anxiety is mostly conducted on the studies of language learning courses. Nevertheless, it could be extrapolated on the text-based training courses, taken in a foreign language, which include both reading and listening activities. Tallon (2009) argues that this form of anxiety is related to both the language-learning and language-using context.

A number of researchers have examined self-efficacy in relation to the language anxiety and found a negative correlation between self-efficacy and language anxiety (Raoofi, Tan and Chan, 2012). It means that the learners who are not sure of their language ability have lower beliefs in their capabilities to successfully pass the training course. Thus, the poor language knowledge could create the language anxiety, which in its turn would negatively affect the learner’s self-efficacy and learning outcomes.

Summarizing that it can be hypothesized that

H1b: The higher language competency of learners positively affects the learning outcomes of e-learning.

2.5.3. Digital Proficiency

Digital proficiency of the learners is one of the variables, used in this research. It refers to the learner's characteristics and is applicable only for digital learning.

The term "comfort level with technology" or "technology readiness" is widely used in the educational segments of scientific literature related to digital learning or e-learning to grasp the tendency of the learners to correctly apply technology at their working place or at home (Colby and Parasuraman, 2001). Hardaker and Smith (2002) mentions "comfort level with technology" as an important factor, affecting learning process.

Evans and Haase (2001) found out that since e-learning is centered around computer technologies, lacking in computer proficiency and good computer skills can become a barrier for learning progress. Individuals who have low technological efficacy are reluctant to try new things and are lacking openness to change. They may perceive using e-learning as a stressor (Sawang, Newton and Jamieson, 2013). Computer self-efficacy is claimed to be one of major determinants of student satisfaction with digital learning and mixed forms of learning (Zhonggen, 2015). It seems important that technology readiness should exist already before the learners start their e-learning courses (Naresh, Sree Reddy and Pricilda, 2016). Low digital competency is mentioned as one of the main factors, which hinder e-learning adoption by organizations in general (Giannakos, Mikalef and Pappas, 2022).

In their study Naresh, Sree Reddy and Pricilda (2016) evaluated a group of 130 university students for interdependencies between different learner's characteristics and comfort level with technology and proved the relation between the latter and the educational background of learners and the frequency of using internet. Lack of knowledge in terms of using computers and generally technology was stated as one of the most noticeable bottlenecks of e-learning implementation. On the other hand, the adaptation and readiness for digital learning were claimed to purely depend on the level of awareness, degree of familiarity with the technology and readiness to accept and adopt the e-learning environment.

Therefore, the following hypothesis outlines the relationship between the digital proficiency and learning outcomes:

H1c: The higher digital proficiency of learners positively affects the learning outcomes of e-learning.

2.6. Organizational Support of E-learning

Speaking further about the "channel" variable, in this thesis it is defined as e-learning without supporting activities and e-learning with supporting activities. By definition, the e-leaning in the form of stand-along course is supposed to be completed by a learner without the interference of a teacher or a trainer. Nevertheless, as described below, for some learners such format could be challenging and learners cannot achieve expected learning outcomes by completing a stand-along e-learning course on their own. In this case a relatively short interference of a trainer can help the learners to cope with the difficulties, appeared during the course, and complete the e-learning module successfully. It is suggested that such a supportive activity can complement the digital learning process, promoting a knowledge transfer. Detailed mechanisms of realization of supporting activities, investigated for the purposes of this work, can be found in the Chapter 3.

This chapter is devoted to the existing research on the mechanisms of organizational support of users when completing e-learning courses.

The question about the effectiveness of knowledge transfer through virtual channels is dwelt on by many scholars. For instance, in their article Prusak and Davenport (1998, p.91) reflect about the move to "virtual offices" as a threatening factor: "While these arrangements offer benefits such as greater employee flexibility and more time with customers, it also lowers the frequency of informal knowledge transfer". And when deciding upon a corporate e-learning strategy, a purely technocentric approach characterizes the very workplace literature that decision-makers are likely to turn to. In this case the focus on technology instead of users leads to the demise of many e-learning initiatives (Servage, 2005). Dearnley (2003) stated that newcomers to nontraditional learning may get lost because they do not know what to do, as there is no detailed guidance from the teacher. Therefore, it is not surprising to see that such learners need to be psychologically prepared for the e-learning environment (Wong, 2007, p. 56).
The proposed solution in this case could be providing access to people with tacit knowledge (Prusak and Davenport, 1998, p. 72). Some scholars argue that "technology facilitates communication but does not replace the instructor" (Sivankalai, 2021, p. 14). In this case the factor of self-efficacy plays an important role. The instructor, providing support, can enhance the level of students' self-efficacy and thus increase their performance accomplishment (Raoofi, Tan and Chan, 2012). In some latest research of applying digital methods in the area of school education by Suzianti and Paramadini (2021) it is recommended to increase teacher awareness of creating a positive learning atmosphere when using e-learning for teaching process through providing extra motivation, respect and personal attention. The authors argue that it helps to reduce learning-related stress factors.

In general, organizational support for e-learning on a higher level can lead to a greater satisfaction and thus also impacts the adoption of such systems. With a speedy implementation of e-learning systems in the organizations, it is important that the employees themselves are motivated to adopt such technologies. In order to achieve this result, they need to receive support and training on how exacly can they correctly and smoothly use e-learning technology (Nelson, 1990). "Organizations adopting e-learning need to examine the support requirements of the potential learners, and, where necessary, have resources for that support in place" (Sawang, Newton and Jamieson, 2013, p. 100). Giannakos, Mikalef and Pappas (2022, p. 622) also highlight „the importance of organizational, managerial, and job support for utilizing individual and social learning in order to increase the adoption of organizational learning".

In the examples, mentioned above, support was mostly provided by the trainers or teachers. There is also evidence in literature that support by managers and peers also has important role in the organizational learning. Facteau *et al.* (1995) argues that both managers and peers can help trainees in particular while transferring learned skills on the job, and thus acting as "trainers". They have conducted the study of 967 managers in state government agencies and proved a positive correlation between peer support and knowledge transfer and between manager support and pretraining motivation. They have formulated the term "social support of training", referring to the support of supervisors, peers and subordinates and concluded that "in order to encourage effective transfer of training skills, supervisors should strive to foster a climate in which employees' training efforts are supported by their peers and subordinates" (p. 20).

One of the findings of the recent study of Al-Fraihat, Joy and Sinclair (2020) also reveals that learners' supporting activities have a significant and positive influence on perceived usefulness, and perceived satisfaction of the e-learning. The author highlights that supporting students by providing guidance how to use e-learning applications, and solutions for technical issues students could face, leads to generating positive feelings, and influences their overall satisfaction about their learning process.

The ability to overcome technically-related challenges is argued to be an important goal of pretraining support in case of digital learning, described in research. Planned organizational support is important in order to overcome technological barriers, that learners may have (Sawang, Newton and Jamieson, 2013, p. 100). "It would seem that e-learners should receive some type of e-learning training prior to enrolment to avoid any difficulties, especially for individuals without much ICT background" (Wong, 2007, p. 55).

Sawang, Newton and Jamieson (2013) make a conclusion about the multidimensional nature of support required by learners. It should include the training of learners as well as, technical help-desk, and support from their managers to use e-learning. They argue that perceived lack of support can cause serious decrease in learners' motivation to use e-learning as a training and development method. Finally, it is argued that organizational support must become a vital success criteria for e-learning implementation.

Overall literature evidence of the positive effect on the supporting activities not only on the learner satisfaction, which is out of scope of this work, but also directly on the learning outcomes (Facteau *et al.*, 1995; Sawang, Newton and Jamieson), allows us to formulate the following hypothesis:

H2: Support activities improve the learning outcomes of e-learning in the form of online test score.

Exact operationalization of the learning outcomes for the purposes of this thesis, will be discussed in the following chapters.

The next set of hypotheses is aimed at investigating the relationships between the learner's characteristics and the method of delivering e-learning, specifically e-learning without support or e-learning with support activities. Based on the literature research described in the Chapter 2.5, it is assumed that learners' individual characteristics (age, language competency and digital proficiency) affect learning-related stress factors. When discussing the phenomenon of a learner's support, before or during completing e-learning modules, we can clearly see that the existence of supporting activities helps to reduce the learning-related stress level of users (Facteau *et al.*, 1995; Sawang, Newton and Jamieson; Wong, 2007). Thus, it can be concluded, that there is a link between the learners' characteristics, which affect their learning-related stress level and supporting activities, reducing it. In other words, the learners' characteristics affect their need to ask for support when taking their digital learning course. This allows us to hypothesize that

H3: Learner's characteristics influence their decision to take support for e-learning.

H3a: The higher age of adult learners negatively affects their decision to take support for e-learning

H3b: The higher language competency of learners positively affects their decision to take support for e-learning

H3c: The higher digital proficiency of learners positively affects their decision to take support for e-learning

Further, it could be discussed, how supporting activities are classified in the literature.

In the research of Morrison (2003) learner support is compared to the safety net, which helps to save learners when their interaction with the system does not go as expected. The author argues that learners need and deserve as much support as the organization can possibly give. Along with that he defines 4 levels of support: self-help with special online guides and lists of frequently asked questions, technology support for the hardware issues, application support for solving the problems with e-learning software, and content support, when help-desk agents or instructional designers help learners understand unclear aspects of e-learning course. Amon all of them, only the fourth level of support relate to the actual knowledge issues, and the other levels are aimed at solving technical problems. For this thesis we are interested in the supporting activities, which can solve both technical and actual knowledge questions.

Another dimension of classifying supporting activities could be the channel of support delivery. Thus, support methods described above, could happen through personal contact like in the examples above or could also take place online. The example of digital training support, using "online social interactions", is described in the study of Hardaker and Smith (2002, p. 346) as promotion of tacit knowledge sharing and exploratory-based learning. The authors also differentiate between support in the group of students, or in one-to-one modus. For example, digital group support is described by the authors as a collaborative learning through the internet. Special focus is made on the importance of the integration of digitally driven person-to-machine and person-to-person ways of communication (Naresh, Sree Reddy and Pricilda, 2016).

Based on these findings, in my thesis I would like to suggest to structure the types of support, depending on two factors:

1. if the support was provided in person i.e., performed either in a physical meeting of a learner and instructor, or through the digital means of communication (telephone or video-call)
2. if support session was organized for one learner (individual support) or for the group of learners simultaneously (group support). In this research it is operationalized as groups of 1-2 learners, versus groups of 3-10 learners

Based on these two factors, one could differentiate the following types of the e-learning supporting activities:

- Individual briefing in person (physical meeting of 1-2 learners with an instructor)
- In-person (physical) support session for the groups of 3-10 learners
- Individual briefing through means of digital communication (online or phone meeting of 1-2 learners with an instructor)
- Digital support session for the groups of 3-10 learners

Visualizing these types of support, they could be structured as a following matrix, presented on the Figure 3.

FIGURE 3: TYPES OF SUPPORTING ACTIVITIES (OWN DESIGN)

	PERSONAL	DIGITAL
INDIVIDUAL	Individual briefing in person (groups of 1-2 learners)	Individual phone briefing Email/chat
GROUP	In-class support session for the groups of 3-10 learners	Digital support session for the groups of 2-10 learners

Based on the research, described above, it could also be suggested that learner's characteristics could not only affect the decision to take support in general, but also to choose specific type of it. Making further assumptions, one could hypothesize that

H4: Learner's characteristics influence their decision to take specific type of support.

Speaking about e-learning combined with support activities it is not possible to avoid the definition and description of bended learning model.

Garrison and Kanuka (2004) argue that "the increasingly prevalent practice of the convergence of text-based asynchronous Internet-based learning with face-to-face approaches is having a volatile impact on traditional campus-based institutions of higher education" and names this combination "blended learning" (p. 96). Indeed, blended learning became nowadays especially important both in education and in business environment.

For instance, Morrison (2003) mentions that there is a shift from pure e-learning to blended leaning, when traditional training options are used together with internet-based media, to assure better learner-centricity. The author talks about the company's learning value chain, of which e-learning is a part. He believes that blended learning approach and integration of classroom trainings with e-learning modules allows the companies to deal with the fears and a lack of "e-learning skills" of their employees on the way to digital transformation.

According to Garrison and Kanuka (2004) this type of learning is characterized by higher complexity of design compared to pure in-class or online models, as it needs to deal with specific contextual needs and contingencies – instructional design, developmental level and resources. Effective blended learning is achieved in case that online and physical classroom methods are combined considering affective factors and brain mechanisms and thus the learners feel encouraged, what results in better learning outcomes (Zhonggen, 2015). The author argues that blended learning is especially effective in big groups of learners, because this model allows the group to align.

According to Zhonggen (2015), the only disadvantage of blended learning compared to digital learning is the cost factor: blended learning requires trainer's support and is more time-consuming in administration. Thus, it is more expensive, compared to a simple e-learning solution. However, Strother (2002) argues that the multinational companies are usually making decisions in favor of blended learning, despite the higher training costs, comparing to simple e-learning way of delivery.

It can be concluded that a blended learning is a more advanced model of e-learning with combined in-class activities with a proven success. Upon definition e-learning combined with support activities can be considered to belong rather to blended learning design. This method of learning allows organizations to better adapt to learner needs and individual characteristics.

3. Methodology

This chapter is aimed at revealing, what kind of data is used in this study, how the data is collected, how obtained data is to be applied in order to answer the research question. First of all, an overview will be given in the section Data Collection and Sample Description. The detailed description of variables and the way of their operationalization is also a part of this chapter.

3.1. Data Collection and Sample Description

This thesis is based upon quantitative research methodology. The data is derived from the Learning Managements System (LMS) of the Austrian company. The information about the company cannot be publicly disclosed. E-learning courses in question are short obligatory animated e-learning modules about certain corporate policies, such as Code of Conduct, Data Protection, Information Security, Office Safety and the others. All courses have the same learning design approach and similar quality, were produced by the same specialized provider. The full list of e-learning courses is presented in the Appendix 1. Learnings were conducted in the period of January 2020 – June 2021.

E-learning courses were assigned to the learners based on their job profile and responsibilities and the completion of the courses was compulsory. All e-learning courses were available through corporate Learning Management System, accessible with the computers, tablets, or smartphones. Upon completion, a learner had to pass an online assessment (test). If a learner failed to correctly answer 80% of the test questions, she/he was supposed to repeat the training. The learners were allowed to have as many attempts as they needed in order to reach the cut-off target of 80%.

Thus, the Learning Management System contains the information about the test score for every completed learning record. In this case “completed” means that the learner passed the end test with the score between 80% and 100%. In the sample there was also the information about how many attempts was needed for the learner to complete the course. There was no information about incomplete courses with the test score less than 80%.

Every learner could take one or more courses. Nevertheless, for the purpose of this analysis the initial data sample was reduced so, that in the final data sample there was only one training record per person. In case of multiple training records for one and the same learner, the earliest record was selected. It allowed to avoid the effect of the learner’s experience with the previous courses to influence the learning results of the following courses.

Many learners had faced difficulties with a new and technically challenging way of learning. The HR Department of the company decided to offer their employees support in order to assist them in their learning process. These supportive practices were organized as follows: a learner at any case was supposed to take at least one test attempt on his/her own. In case of failure, he/she could at any point (after any unsuccessful test attempt) contact a specially created helpdesk, either by the phone or by email. Helpdesk specialist could help a learner individually and discuss the issue on the phone.

Another way was to organize so called “support session” with several learners at once, if the learners chose so, for example, if a group of learners had similar problems or were located on the same site. At this session employees could absolve e-learning on a personal or a company smartphone or tablet after a short briefing from the instructor and with the instructor’s support along the way.

Eventually, every learner could either pass e-learning without assistance, or request assistance and pass e-learning after receiving it. The decision, what type of support to choose, was made by learners. It is assumed that a learner always successfully passed the test after the support session, because the specialists, providing support, were instructed to control the test attempt after the support session and make sure that the test is passed. It means that for the learners, who took support, the number of the attempts minus one identified the moment, when a learner decided to take support. The data from the helpdesk log (type of support) was provided for this research and included into the data sample.

Supporting activities in general received good feedback from the learners. But the question, if such kind of support allows to significantly improve learning outcomes, was still open.

3.2. Operationalization of Variables

The data set, derived from a Learning Management System and reduced so that there is only one the earliest training record per person, contains totally 640 records with the following data to every learning record:

- Learner unique ID-number
- Learner date of birth
- Learner job role
- Learner nationality
- The highest niveau of German language course for foreign nationals
- Name of e-learning
- Number of attempts till 80% score was achieved
- Test score (80% to 100%)

The database contains the records only about the successful attempt to each course, which is the last attempt as well. General overview of all the variables, used in this thesis, can be found in the Appendix 2.

3.2.1. Outcome Variables

In this section we introduce the set of variables, operationalizing the term “learning outcomes” and “the choice of learning method”.

Most of the courses can be described as compliance learning. In his book “Fully Compliant: Compliance Training to Change Behavior” Waugh (2019) defines the compliance training as any learning activity (course, program, etc.) aimed at addressing a specific legal risk and supporting the culture and ethics generally and within organization. The e-learning courses, considered in this work, deal with the topics of work safety, information security and code of conduct and are created to manage the risk of unsafe or unethical behavior of the employees. The main aim of this training setup in general is to maintain a certain culture, when all the employees are accountable and empowered to make safety and ethical decisions on their own. The author generally concludes that satisfactions or “smiley” surveys, matching Kirkpatrick’s Level 1 evaluation show very limited usefulness in case of compliance trainings, when learners need to “know” rather than to “like”. He argues that though “it is satisfying to know that participants enjoyed a session, but that enjoyment does not necessarily correlate with lasting learning transfer or behavior change”. The author claims assessments to be an effective measure of learning efficiency for compliance trainings and offers to assess the training efficiency using training simulations and scenarios. This matches the interactive situational questions in the tests, which were offered the learners in our study in the online tests.

Related to the four-factor learning evaluation model of Donald Kirkpatrick (1953), such type of evaluation would describe the level 2 of the module i.e., a measure of learning or how the learner has managed to grasp it.

Learning outcomes for the purpose of this work are assessed only in the aspect of immediate understanding the content of the learning course right after the learning. After completing the e-learning module, a learner has to pass an integrated online test. Every test contains from 5 to 10 multiple choice questions, including situational or simulation questions, related to the topic of the course. A learner has to score at least 80 % to successfully complete the course. That is why the range of values for this variable is from 80% to 100%. Given the distribution of data with 273 out of 640 learners scored 80% and 186 learners scored 100%, we can see that the majority of data points are located at the two extreme points (Table 1). That is why it was suggested to group the values and add one more categorical ordinal variable *score*.

TABLE 1: TEST SCORE DISTRIBUTION IN THE SAMPLE (N=640)

Score Level	Description	Number of learning records in the sample n=640
1 – maximal score	100%	273 (43%)
2 – medium score	More than 80%, but less than 100%	181 (28%)
3 – low score	100%	186 (29%)

One more variable, characterizing the learning outcomes is the number of *attempts* before the test is passed. Number of attempts is directly connected with the number of failed tests, that is why it can characterize the learning results. For the organization the number of attempts is also connected with the paid working time required to pass the training. That is why it could be important to identify the factors, which could influence and the number of unsuccessful test attempts and investigate the methods of reducing it. The number of attempts in the sample varies from 2 to 7 and is treated as an ordinal categorical variable with natural ordering (Table 2). Using in this case categorical variable rather that continuous, helps us to make this data more descriptive in our analysis and the interpretation simpler. We can also easily take assumption that successive categories of our ordinal independent variable *attempts* are interval scaled.

Originally, there were the random instances of 8-10 attempts, which were removed as outliers.

TABLE 2: DISTRIBUTION OF THE NUMBER OF TEST ATTEMPTS COMPETENCY IN THE SAMPLE (N=640)

Number of Attempts	Number of learning records in the sample n=640
1	301 (47%)
2	149 (23%)
3	83 (13%)
4	34 (5%)
5	33 (5%)
6	17 (3%)
7	23 (4%)

The dependent variable “channel of knowledge transfer” is defined firstly as *e-learning without support* or *e-learning with support*.

The sample was supplemented with the binary variable *support*, depending on the wish of a learner to seek for the support at all. The value of this variable was defined as 1 if a learner has asked for and received support after failing by any number of the attempts to compete the test (117 out of 640 training records) and as 0 in case that a learner has neither asked nor received the support and completed the test on their own, independent on the number of the successful attempt (523 out of 640 training records). Learners were allowed to ask for the support only if they failed at least once. Consequently, if they succeeded at the first attempt and the number of attempts was equal to 1, the value of the variable *support* was always 0.

Secondly, the actual type of support was specified according to the model, presented in the previous chapter on the Figure 3. Two dimensions of support, digital versus personal and individual versus group, were operationalized as two binary variables *digit_pers* and *ind_group* as follows in the sample (n=117), containing only the training records with support (Table 3):

TABLE 3: NUMBER OF LEARNING RECORDS PER TYPE OF SUPPORT IN THE SAMPLE (N=117, RECORDS WITH SUPPORT)

digit_pers → *ind_group* ↓	1 – a learner has asked for and received their support through digital means of communication	0 – a learner has asked for and received their support on a personal meeting (in presence)
1 – a learner has asked for and received their support individually	26	29
0 – a learner has asked for and received their support in a group	33	29

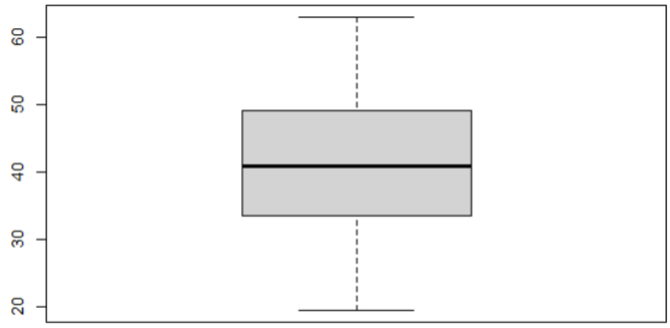
3.2.2. Independent Variables

The following independent variables are in the focus of this study:

- Age of learners
- Language competency
- Digital proficiency

Age of learners is identified on the basis of the date of birth. Average age of the learners in the sample (n=640) is equal to 41.18 years. About 25% of learners are younger than 34 years, the age of about 25% is between 34 and 41 years and about 25% are older than 41 and younger than 49 years. The rest quarter of learners have the age between 49 and 65 years. Standard deviation is equal to 9.9, mean is 41.4. This distribution is graphically represented on the Figure 4.

FIGURE 4: BOXPLOT OF THE VARIABLE AGE OF LEARNERS (N=640, FULL SAMPLE)



Language competency is defined as a factor variable, based on the information about the nationality of learners and the highest level of German language course for foreign nationals (Table 4). The category 1 was assigned to the nationals of German-speaking countries by default. For the nationals of the other countries category 1 was assigned to those, who had the certificate of language proficiency with levels C1-C2. Category 2 was assigned to the learners with A2, B1 and B2 language niveau and category 3 – to those, possessing the certificate of level A1 or no certificate. For learners with no certificate, the job role was referred to for control. In a few cases when the job role required higher level of German language, but the data of the language certificate was missing, the assumption of a higher language competency was made. There are certain limitations of this method of categorization, specifically, related to the citizens of the German-speaking countries. Actually, some of them could have the level of German language less than C1. This possibility was considered to be negligible for the purpose of these study.

TABLE 4: DISTRIBUTION OF LANGUAGE COMPETENCY IN THE SAMPLE (N=640, FULL SAMPLE)

Language Competency Level	Description	Number of learners in the sample
1 – high language competency	Nationals of German-speaking countries, C1-C2 level of German language	514 (80%)
2 – medium language competency	German language certificate, level A2, B1 and B2	36 (6%)
3 – low language competency	German language certificate, level A1, or no certificate	90 (14%)

Digital proficiency of learners was addressed through the information about their job roles. Consequently, following categories were extracted according to the computer skills, required to perform a certain job role (s. Table 5). The important factor for categorization was the average share of computer-based working time, compared to the total working time per job role. The assumptions were based on the expert opinion of the specialists of HR department. Finally, the categories of digital proficiency were defined as follows:

TABLE 5: DISTRIBUTION OF DIGITAL PROFICIENCY IN THE SAMPLE (N=640, FULL SAMPLE)

Digital Proficiency Level	Related Job Roles	Computer-based Working Time, %	Number of learners in the sample
1 – high digital proficiency	all office roles, second-line managers in operations and technical specialists	over 50 %	349 (55%)
2 – medium digital proficiency	operations managers, specialist in operations, apprentice	below 50 %	170 (27%)
3 – low digital proficiency	front line jobs, team leaders in operations	do not use computer at work	121 (19%)

Major limitation of this categorization is that the linking of job role to the digital proficiency could not always be accurate: e.g. a student with the high digital proficiency could have a front line job. Nevertheless, this possibility was considered negligible for the given sample.

3.2.3. Control Variables

According to (KPMG, 2015) the quality of the e-learning modules plays an important role in the sustainability of learning. Although all the courses, considered in this study, were produced by the same provider and thus possess similar technical quality, it is logical to assume, that different content topics can be understood differently by various groups of learners. Some topics could be perceived as more difficult, compared to the others, depending on various learner's characteristics.

It can be assumed that there is a variable, which significantly influences the dependent variables, though is not a focus of the study on its own. This variable should be taken into the model as a control variable. Deriving from research done in this topic, there is reason to believe that the type of the e-learning course and thus the learning group could also influence the outcome and has to be kept constant.

To address this issue different e-learning courses were grouped based on the expert opinion about the similarity of content and learning goals. The group overview is presented in the Appendix 1.

Totally, there are three course groups in the final sample (n=640). These are:

- *Group – Conduct* (210 records), which includes the e-learning modules about the Code of Conduct for the office and front-line employees
- *Group – Data* (363 records), which includes the topics of Data Protection, Information Security and Data Management
- *Group – Safety* (67 records), with the modules related to various Health, Safety and Environment topics

The variable *course_group*, containing these 3 values, is included into the analysis as a control variable.

4. Empirical Analysis

An overview of the empirical study applied in this master's thesis is described in this chapter. The purpose of this chapter is to present the findings of the quantitative data analysis of the main empirical study. The analysis was performed, using R programming language for statistics.

4.1. Descriptive Statistics

As a preparation for the analysis the descriptive statistics overview of the initial sample was made. The results of this overview for the described above sample of 640 training records (Sample 1) is presented in the Table 6. More detailed information for the Sample can be found in the cross-tabs in Appendix 3.

TABLE 6: DESCRIPTIVE STATISTICS FOR THE SAMPLE 1, SAMPLE 2 AND SAMPLE 3

Sample 1 (full sample)		Sample 2 (> 1 attempt)		Sample 3 (1 attempt)	
Characteristic	**N = 640**[1]	**Characteristic**	**N = 339**[1]	**Characteristic**	**N = 301**[1]
age	41 (34, 49)	age	42 (34, 50)	age	40 (32, 49)
digital_prof		digital_prof		digital_prof	
1	349 (55%)	1	155 (46%)	1	194 (64%)
2	170 (27%)	2	96 (28%)	2	74 (25%)
3	121 (19%)	3	88 (26%)	3	33 (11%)
language		language		language	
1	514 (80%)	1	263 (78%)	1	251 (83%)
2	36 (5.6%)	2	22 (6.5%)	2	14 (4.7%)
3	90 (14%)	3	54 (16%)	3	36 (12%)
support		support		support	
0	523 (82%)	0	222 (65%)	0	301 (100%)
1	117 (18%)	1	117 (35%)		
score		score		score	
1	273 (43%)	1	134 (40%)	1	139 (46%)
2	181 (28%)	2	96 (28%)	2	85 (28%)
3	186 (29%)	3	109 (32%)	3	77 (26%)

Sample 1 (full sample)		Sample 2 (> 1 attempt)		Sample 3 (1 attempt)	
attempts		attempts		attempts	
1	301 (47%)	2	149 (44%)	1	301 (100%)
2	149 (23%)	3	83 (24%)	course_group	
3	83 (13%)	4	34 (10%)	Group - Conduct	93 (31%)
4	34 (5.3%)	5	33 (9.7%)	Group - Data	169 (56%)
5	33 (5.2%)	6	17 (5.0%)	Group - Safety	39 (13%)
6	17 (2.7%)	7	23 (6.8%)	[1] Median (IQR); n (%)	
7	23 (3.6%)	course_group			
course_group		Group - Conduct	117 (35%)		
Group - Conduct	210 (33%)	Group - Data	194 (57%)		
Group - Data	363 (57%)	Group - Safety	28 (8.3%)		
Group - Safety	67 (10%)	[1] Median (IQR); n (%)			
[1] Median (IQR); n (%)					

Further the training records for the cases, when learners passed the test at the first attempt, were dropped. In these cases, learners had no difficulties with the e-learning and did not need support. They did not have to make the decision, if they would ask for support or not. For all the training records with the number of attempts above 1, learners failed the first time and hade to make this decision. These are the training records, which were used in most of the cases for this study. Descriptive statistics for this smaller sample (Sample 2) of 339 training records represented in the Table 6. Further in the analysis I also use the Sample 3 (n=301), which contains only the training records with the variable *attempts* equal to 1, demonstrating the learners, who have passed their course tests at the very first attempt. Obviously, the Sample 1 is the combination of Samples 2 and 3.

Describing the dependent variables, first the variable *score* can be highlighted. This is a categorical ordinal variable with the value 1, equivalent to 100% test score (273 records in the Sample 1), 2 corresponding to any value, which is more than 80 and less than 100 (181 records in the Sample 1) and 3 – to the test score 80% (186 records in the Sample 1). We can see, that the course test scores look averagely better for the group of learners, who passed the test at the first attempt, compared to the rest of the sample. It shows, that the learning performance got worse with increasing the number of attempts.

As for the dependent variable *attempts*, representing the number of attempts required to score at least 80 per cent by the test, one can see that the biggest group of 301 records (or 48% of total) represents 1 attempt, then comes the group of 2 attempts (149 records) and 3 attempts (83 records). Further the number of records gradually decreases. The records with the number of attempts more than 7 were excluded from the sample.

Having a look at the independent variables in all 3 samples, one can notice, that comparing to the initial Sample 1, in the Sample 2 with no records with 1 test attempts, the average and maximum age of learners has got 1 year higher: from 41 to 42 and from 49 to 50 years respectively. It can be concluded, that a part of the youngest learners has successfully completed the course with the first attempt. Standard deviations for the variable *age* are pretty close for all 3 samples: Sample 1 – 9.91, Sample 2 – 9.87, Sample 3 – 9.89. It indicates the results are close to the mean.

For the variable *digital_prof* the biggest share of learning records in Sample 1 (55%) represents the highest digital proficiency of learners, which decreases to 46% for Sample 2 and increases to 64% for Sample 3. It proves that a sufficient group of learners with the highest digital proficiency passed the test from the first attempt. Same logic applies to the level 3 of this variable: in increases from 19% for Sample 1 to 26% for Sample 2 and decreases to 11% for Sample 3, demonstrating that the learners with the worst digital proficiency required more than 1 test attempt. The values of the level 2 are more stable. It can be observed that the share of learners with the worse digital proficiency is the smallest in all 3 samples.

As for the variable *language*, the picture is not as obvious: we see the same tendency, but the values of differences between the Samples per level are much more moderate and stay within 3%. The share of the language competency of level 2 stays the smallest in all 3 samples (from 4.7% in Sample 3 till 6.5% in the Sample 2).

In the Sample 1 the split between the values of binormal variable *support*, representing the fact of support during the training, is 82% (did not ask for support) versus 18% (asked for support). Nether in the Sample 3 needed supporting activities, because they managed to pass the test at once. Thus, in the Sample 2 with excluded records, belonging to Sample 3, the share of records with support increased from 18% to 35%. The share of learners, asked for support, predictably increased for the Sample 2.

When doing regression analysis, the variable course-group will be treated as a control variable. Hence, there is also the descriptive statistics per group of learning courses. It can be observed, that the number of training records in the group Data is the biggest (363 or 57% in the Sample 1) and in the group Safety is the smallest (10% in the Sample 1). The records of one more course group were excluded from the sample, because after removing records of the same learners, the number of records in this group got less than 30.

Having the main dependent variable score as ordinal categorical variable, before performing ordinal logistic regression, we need to check for the existence of proportional odds. By proportional odds it is considered that the independent variables have the same effect on every dependent variable level (Belsley, 1991).

We use the ordinal variable *score* as our outcome variable. We would like to calculate the frequency and mean of it. Its frequency is 273 (score=1), 181 (score=2) and 186 (score=3) in the Sample 1. Its mean equals to 1.864. From the output, it's clear that *score* has higher proportion in higher end, which results in a higher mean value 1.864.

Further I would like to investigate the factors, interesting for the analysis and find out, whether they will have potential effects on the outcome variable score. For that I calculate the cross-tabs for the score versus chosen independent variables (s. Appendix 3). The analysis for the proportional odds, meaning that the relationship between each pair of outcome groups is the same, and the relationship between all pairs of groups can be described with one model, will be done, using the Brant Test (Brant, 1990) for each of tested *polr* models.

It is also important to consider the existence of correlations among independent variables – multicollinearity (Belsley, 1991; Freund, 2006). For example, it would be reasonable to suggest the collinearity between age and digital competency of learners. Checking the Spearman's correlation coefficient, I get the value 0.142 for the pair digital proficiency – age, -0.109 for the pair language competency – age and 0.195 for language – digital proficiency. The values are relatively small and indicate only insignificant correlation.

4.2. Analysis

4.2.1. Hypothesis H1

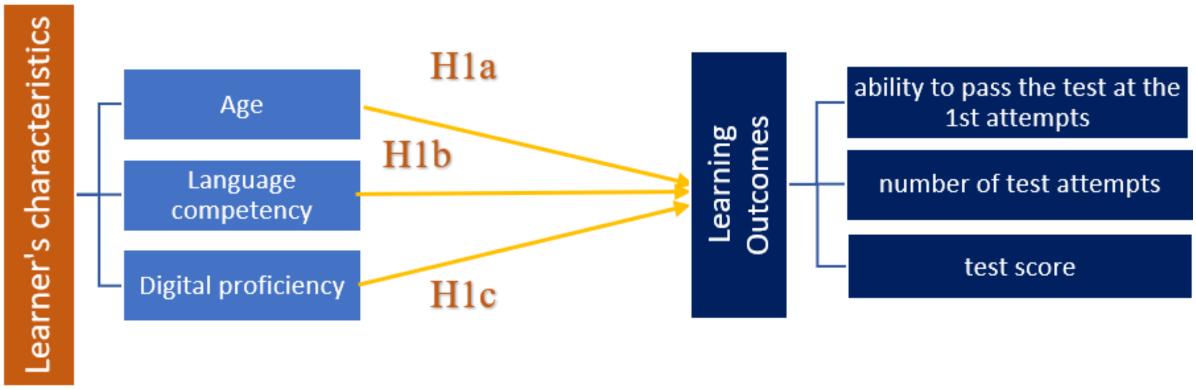
As described in the literature overview and in the chapter 3.2.1, the learning outcomes for the purposes of this study will be operationalized as the score of the final test, which a learner takes after completing e-learning module. Waugh (2019) argues that to assess the efficiency of so-called "compliance" or mandatory training it is the most reasonable to use situational questions, same as used in the assessments in the studied learning modules. Additionally, we have the data, if a learner managed to pass the test at the first attempt or not. Obviously, it can also be considered as a reliable learning outcome and is subject to further analysis.

This evaluation can be linked to the level 2 of Donald Kirkpatrick's model as a measure of the learner's actual understanding of the course content. I would like to investigate the dependencies between the learning outcomes in the form of the test score, ability to pass the test at the first attempt and the number of test attempts and such demographic variables as the learner's age, language competency and digital proficiency. The variable *age* is numeric, the variables *language competency* and *digital proficiency* are categorical ordinal variables with level 1 – the best and level 3 – the worst value.

In the literature overview I also refer to possible difference in the dependencies between the learning outcomes of children and adult learners. In my study with respect to the age of learners I focus on the adult learners.

Thus, with the first set of hypotheses, visualized on the Fig 5. I would like to find out, if the learners' characteristics actually affect the learning outcomes or, formulating it otherwise, if the age of the learners, their language competency and digital proficiency are correlated with their test scores, influence their ability to pass test at the first attempts and generally the number of attempts they need to get on the test 80 % or more.

FIGURE 5: CONCEPTUAL MODEL FOR H1 (OWN DESIGN)



First of all, it was checked, how the learners' characteristics influence the ability of learners to pass e-learning from the first attempt at all. Data sample for this test contains all learning records (Sample 1, n=640) with dependent variable *first_attempt* (1 – passed at the 1st attempt, 0 – passed at any further attempt). Sample size is 640 training records, out of which 301 passed the test from the first attempt. In 339 training records more than 1 attempt was required to pass the test. I check 2 models: first – without control variable *course_group*, and second – including this variable.

Code in R:

log_reg_1 <- glm(first_attempt ~ age + language + digital_prof + course_group, data = elearning_h1_640, family = 'binomial')

In the Table 7 we can see that though control variable *course_group* does not prove to be statistically significant on its own, adding this variable decreases Log Likehood coefficient with almost the same AIC value, what shows that this variable does not have much influence.

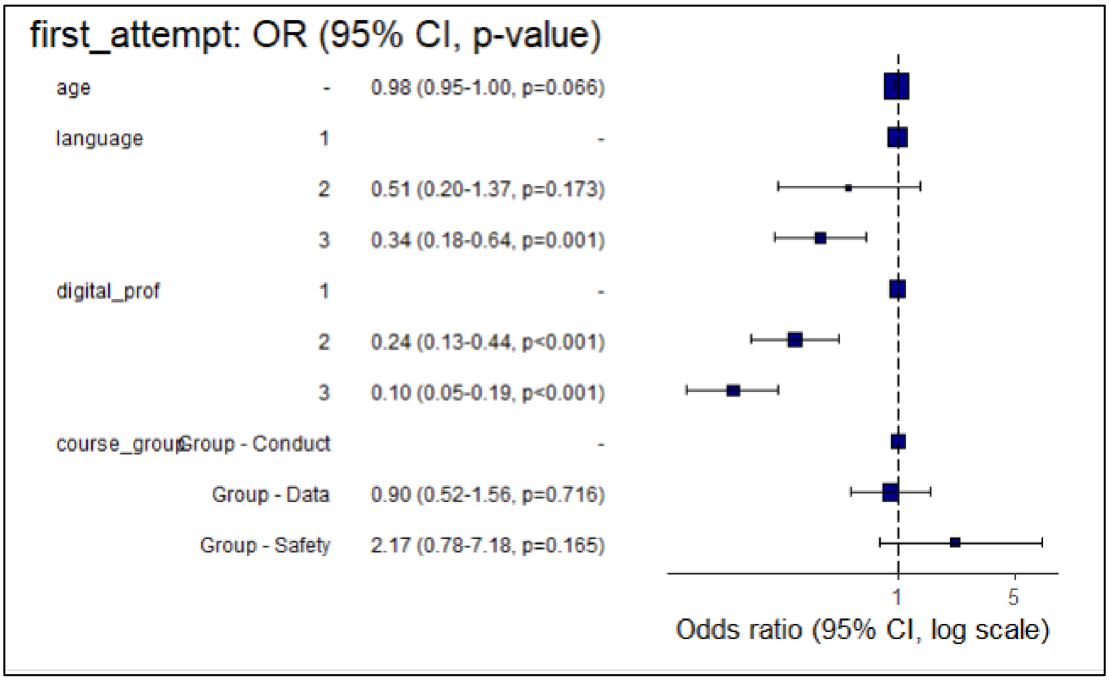
To measure the significance of the overall model, it was tested, whether the model with predictors fits significantly better than a model with the intercept only (H0). We calculate the difference between the residual deviance for our hypothesis (model with predictors) and null-model. We need to find distributed chi-squared with same degrees of freedom as the difference between the current and the null model degrees of freedom. These test results allowed us to define the difference in deviance for the two models, which equals 100.73. Degrees of freedom two models difference represents the number of predictor variables in the model and were calculated equal to 7. The associated p-value of the model is 7.621666e-19, what tells us that our model fits significantly better than the null model. It can be concluded, that the ability to pass the knowledge test after e-learning at the very first attempt highly depends on the digital proficiency of learners as well as on their age and language competency.

TABLE 7: RESULTS OF LOGISTIC REGRESSION FOR DV FIRST_ATTEMPT (N=640, FULL SAMPLE)

Log. Reg. H1, no controls, N = 640		Log. Reg with controls, H1, N = 640	
	Dependent variable:		*Dependent variable:*
	first_attempt		first_attempt
age	-0.023*	age	-0.024*
	(0.013)		(0.013)
language2	-0.672	language2	-0.672
	(0.491)		(0.493)
language3	-1.110***	language3	-1.068***
	(0.317)		(0.320)
digital_prof2	-1.367***	digital_prof2	-1.412***
	(0.303)		(0.308)
digital_prof3	-2.329***	digital_prof3	-2.255***
	(0.320)		(0.322)
Constant	3.232***	course_groupGroup - Data	-0.102
	(0.588)		(0.279)
Observations	**640**	course_groupGroup - Safety	0.775
Log Likelihood	-199.048		(0.558)
Akaike Inf. Crit.	410.097	Constant	3.263***
Note:	*p<0.1; **p<0.05; ***p<0.01		(0.620)
		Observations	**640**
		Log Likelihood	-197.451
		Akaike Inf. Crit.	410.903
		Note:	*p<0.1; **p<0.05; ***p<0.01

The odds ratio for each predictor variable can be calculated by using the formula e^{β}. Odds ratio is reverse to probability. One can notice that the variable *language2* is not significant in the model. It was discovered that holding the other parameters constant, the odds of passing the test at the first attempt decreased by 2% for each additional year of age, decreased by 66% for level 3 compared to level 1 of language competency, by 75% for learners with digital proficiency level 2 compared to level 1 and by 90% with level 3 compared to level 1. All values of the odds ratio with the confidence interval 95% are presented on the Figure 6.

FIGURE 6: ODDS RATIO PLOT FOR DV FIRST_ATTEMPT (N=640, FULL SAMPLE)



As a next step, I perform one more test of H1 with the number of attempts (variable *attempts*) as dependent variable and learners' characteristics – as independent variables, without taking support into account (Table 8). We know, that for the records, containing support, the last attempt always ended with the course completion. It means that the previous attempt could be taken into the sample for the purposes of this test. Thus, for the records, containing support information, we calculate the number of attempts as follows: *attempts = attempts-1*. For this test we do not consider the learners, who passed the test at the first attempt. We also take out the outliers, the records with the number of attempts more than 6 (14 records). Final number of the training records in the sample – 339. Brant test for this model shows that the proportional odds assumption is not violated, though for digital proficiency probability is close to 0.05. The model is assumed as valid for this data set.

Residual Deviance of the model turned to be 1742.3 and AIC is equal to 1764.3. When adding the variable *course_group* to the model, AIC slightly increases to 1765.3, thus the model is kept without controls.

Code in R:

ord_log <- polr(attempts ~ age + language + digital_prof, data = elearning_h1_339, Hess=TRUE)

TABLE 8: RESULTS OF THE ORDINAL LOGISTIC REGRESSION FOR DV ATTEMPTS (N=339, >1 ATTEMPTS)

Log Reg. H1, DV attempts, N=339	
	Dependent variable:
	attempts
age	0.023**
	(0.010)
language2	-0.732
	(0.448)
language3	-0.261
	(0.300)
digital_prof2	0.456*
	(0.236)
digital_prof3	-0.214
	(0.262)
Observations	339
Note:	*p<0.1; **p<0.05; ***p<0.01

Only the variables *age*, *digital_prof2* are statistically significant in the model. It can be concluded that the number of test attempts depends only on the age and on the digital proficiency of learners.

To make it easier to interpret logistic regression models I convert the coefficients into odds ratios by exponentiating the estimates and confidence intervals. As a result, it can be concluded that the odds of passing the test after more attempts increased by 2% for each additional year of age and also increased by 58% for learners with worser digital proficiency of level 2 compared to level 1, but those at level 3 are not significantly different from level 1.

We could see it more in detail on the cross tabulation on the Fig. 7. For example, one can notice that the share of the learners, passing the test at 2-4 attempts is 89% for the group with digital proficiency level 1 and only 68% for the group with digital proficiency level 2. It is interesting to notice, that for the group with the worst digital proficiency level 3 the share of learners, passed the test with the smaller number of attempts increased, comparing to level 2 group, and got equal to 72%. It could be suggested that the learners with the highest and lowest digital proficiency tend to pass the test with less attempts, comparing to the group with level 2. We could assume, that there is a certain impact of the availability of support offer, especially in case of the group with the worst digital proficiency (level 3).

FIGURE 7: CROSS-TABULATION FOR DIGITAL PROFICIENCY VERSUS ATTEMPTS (N=339, 1 ATTEMPT)

Cross-Tabulation for Digital Proficiency vs Attempts

attempts	*digital_prof* 1	2	3	***Total***
2	74 49.7 %	34 22.8 %	41 27.5 %	149 100 %
3	44 53 %	21 25.3 %	18 21.7 %	83 100 %
4	20 58.8 %	10 29.4 %	4 11.8 %	34 100 %
5	9 27.3 %	14 42.4 %	10 30.3 %	33 100 %
6	3 17.6 %	7 41.2 %	7 41.2 %	17 100 %
7	5 21.7 %	10 43.5 %	8 34.8 %	23 100 %
Total	155 45.7 %	96 28.3 %	88 26 %	339 100 %

χ^2=23.887 · df=10 · Cramer's V=0.188 · Fisher's p=0.005

As a next step, we would like to see the correlation between the test score and the independent variables: age of learners, language competence and digital proficiency. As the variable *score* is ordinal (grouped in 3 categories with the test scores of 80%, 80-100% and 100%), I apply ordinal logistic regression to the group of learners, who passed the course test on the first attempt. This group is not influenced by support activities: no one, passed at the first attempt took support during the training. The sample size for this group of learners is 301. Brant test for this dataset also confirms the proportional odds assumption and model validity.

First of all, I test the model only with independent variables *age*, *language* and *digital_prof*, but without control variables, on the second – with all independent and control variables included (Table 9).

Code in R:

ord_log1 <- polr(score ~ age + language + digital_prof, data = elearning_h1_301, Hess=TRUE)

ord_log2 <- polr(score ~ age + language + digital_prof + course_group, data = elearning_h1_301, Hess=TRUE)

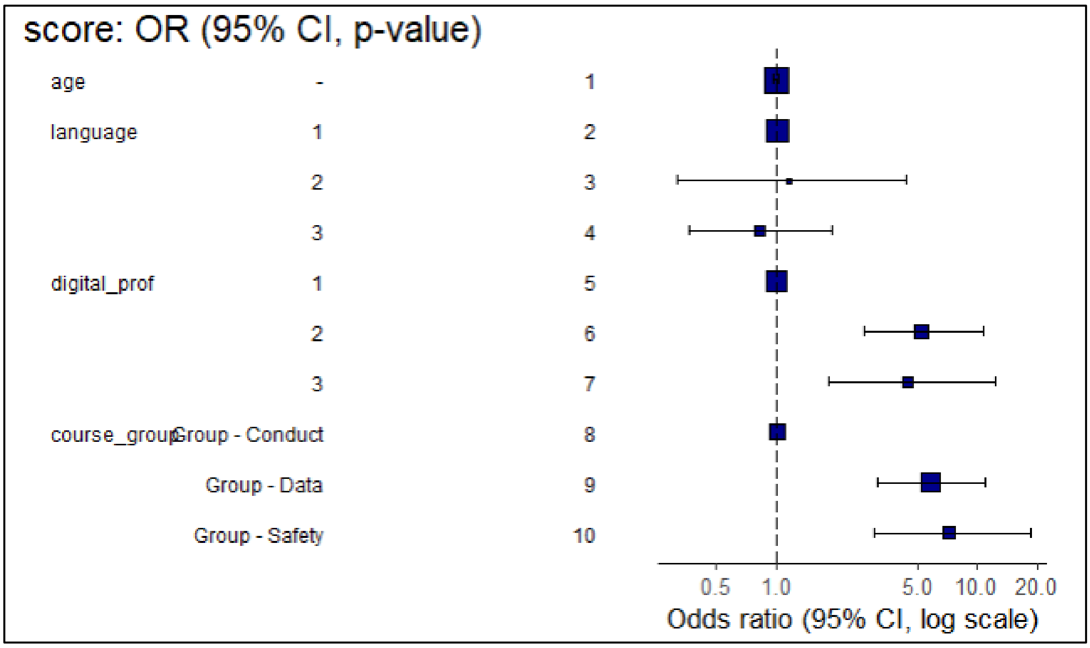
TABLE 9: RESULTS OF ORDINAL REGRESSION FOR H1 FOR DV SCORE (N=301, 1 ATTEMPT)

Ordinal Reg. H1, DV score, N=301		
	Dependent variable:	
	score	
	(1)	(2)
age	-0.010	-0.011
	(0.011)	(0.012)
language2	0.172	0.345
	(0.523)	(0.546)
language3	-0.262	-0.383
	(0.336)	(0.363)
digital_prof2	0.913***	0.997***
	(0.251)	(0.271)
digital_prof3	1.022***	0.627*
	(0.339)	(0.362)
course_groupGroup - Data		2.095***
		(0.294)
course_groupGroup - Safety		1.402***
		(0.371)
Observations	301	301
Note:	*p<0.1; **p<0.05; ***p<0.01	

One can notice, that the relation between the test score and the course groups is highly significant, whereas among our independent variables only digital proficiency plays an important role, influencing the test score, and neither age nor language competency of learners do not improve the model. Comparing the AIC values of these two models (AIC for the model with controls equals 579.9, without - 635.4), and their residual deviance (561.9 with controls, and 621.4 – without), we can conclude that the model with controls fits the data better.

Reviewing the coefficients' table, it can be concluded when improving the digital proficiency of learners from level 3 to level 1, we would expect a 0.62 increase in the expected value of the test score, and from level 2 to level 1 – even the increase of 0.99 in the log odds scale (or in 2.7 and 1.9 times), given that all of the other variables in the model are held constant. For the variable *language* the 95% CI crosses 0, what makes it statistically insignificant (Fig 8). It can be concluded that the test score highly depends on the digital proficiency of the learners.

FIGURE 8: ODDS RATIO PLOT FOR DV SCORE (N=301, 1 ATTEMPT)



On the next step I perform the same tests on the sample with excluded training records, where the learners passed the test on their 1st attempt (Sample 2, N=339). The calculation tables can be found in the Table 10. Overall tendencies stay the same for this sample, with the exception that the variable *age* has got statistically significant in addition to the variable *digital_prof*. The odds of having the test result less than 100% increased by 2% for each additional year of age and also increased in 3.12 for learners with digital proficiency level 2 compared to level 1 and in 3.48 times with level 3 compared to level 1.

Based on the analysis we can again conclude that the test scores are highly influenced by the digital proficiency of learners. We could also suggest that the factor of age starts to play an important role in test results after the learners fail the first attempt and get exposed to the possibility of an offered support.

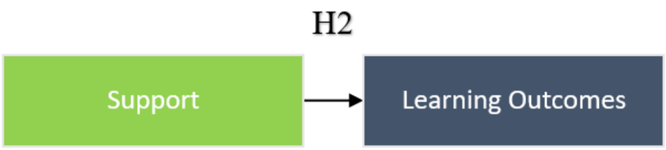
TABLE 10: RESULTS OF ORDINAL REGRESSIONS FOR H1 FOR DV SCORE (N=339, >1 ATTEMPT)

Ordinal Reg. H1, DV score, N=339		
	Dependent variable:	
	score	
	(1)	(2)
age	0.023^{**}	0.019^{*}
	(0.011)	(0.011)
language2	-0.386	-0.317
	(0.415)	(0.430)
language3	0.002	0.212
	(0.292)	(0.304)
digital_prof2	1.003^{***}	1.138^{***}
	(0.251)	(0.270)
digital_prof3	1.262^{***}	1.247^{***}
	(0.269)	(0.290)
course_groupGroup - Data		1.293^{***}
		(0.232)
course_groupGroup - Safety		1.253^{***}
		(0.408)
Observations	339	339
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

4.2.2 Hypothesis H2

When testing this hypothesis, I come directly to answering to my research question and would like to find out, if the addition of support activities from the side of the competent colleague (HR specialist, trainer or a manager) allows the learners to improve their learning outcomes. In this case as learning outcomes, I first use the test score. I would like to test a model from the Hypothesis 1 and add one more independent binary variable *support* with the values 1 (learners took the support) and 0 (learners did not take the support), s. Fig 9.

FIGURE 9: CONCEPTUAL MODEL FOR H2 (OWN DESIGN)



As mentioned above, I investigate the test score as a learning outcome. For the analysis I consider only the group of learners, who passed the test after more than 1 attempt (Sample 2), as they were potentially exposed to the offer of support (Table 11). The number of training records in this sample equals to 339, out of which 117 records are with and 222 records without support and there are no training records with less than 2 test attempts. Brant test for this model confirms its validity (Omnibus>0.05).

Code in R:

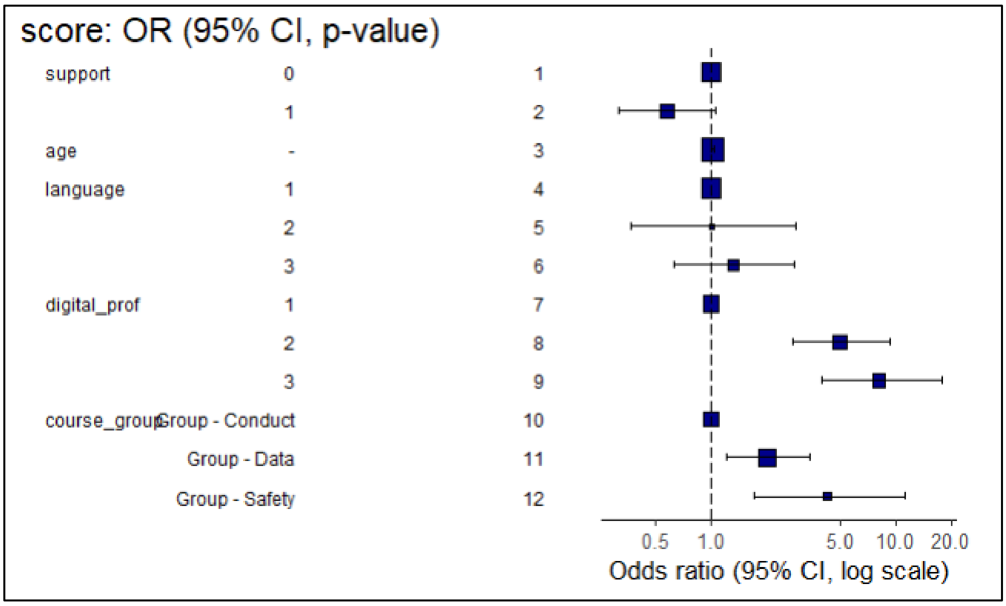
ord_log_h2_1 <- polr(score ~ support + age + language + digital_prof + course_group, data = elearning_h2, Hess=TRUE)

TABLE 11: RESULTS OF ORDINAL REGRESSIONS FOR H2 FOR DV SCORE (N=339, >1 ATTEMPT)

Ordinal Reg. H2 with support, N=339	
	Dependent variable:
	score
support1	-0.435*
	(0.258)
age	0.021*
	(0.011)
language2	-0.265
	(0.433)
language3	0.358
	(0.318)
digital_prof2	1.227***
	(0.275)
digital_prof3	1.428***
	(0.312)
course_groupGroup - Data	1.322***
	(0.233)
course_groupGroup - Safety	1.241***
	(0.405)
Observations	339
Note:	*p<0.1; **p<0.05; ***p<0.01

Looking at the Table 11 and keeping in mind that the dependent variable score is categorical, with the value 3 indicating the worst possible score when passing the test (80%) and value 1 for the 100% test score, the demonstrated negative coefficient of logistic regression tells us that the learners, who took support, scored better at the test within the same course group. One can notice that also age of learners and their digital proficiency, as well as the course group make huge impact on the test performance. Describing the probabilities, it can be mentioned that odds of having the test result less than 100% decreased by 35% for the learners who took support, increased by 2% for each additional year of age, increased in 3.4 times for learners with worser digital proficiency level 2 compared to level 1 and in 4.2 times with level 3 compared to level 1 (Fig. 10).

FIGURE 10: ODDS RATIO PLOT FOR H2, DV SCORE (N=339, >1 ATTEMPT)

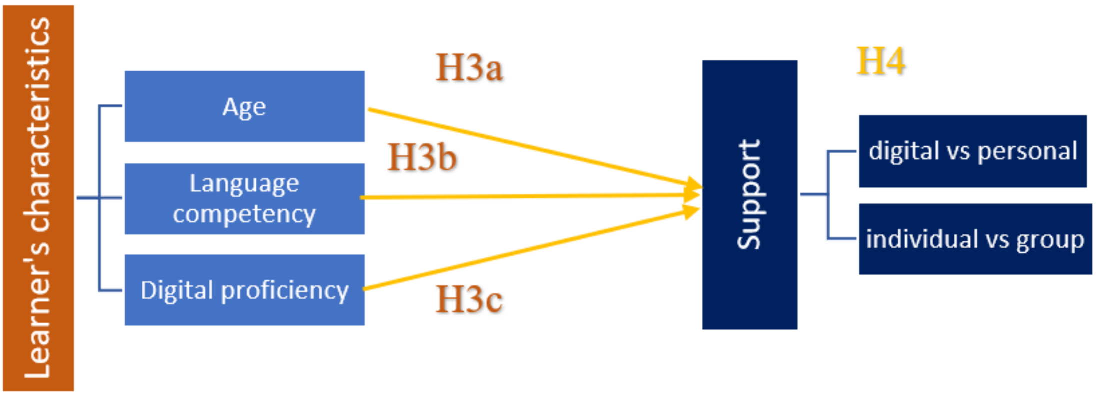


These observations highlight the importance of the learners' decision to take support and make us continue investigating supporting activities further.

4.2.3 Hypothesis H3

With the third and the fourth hypothesis I would like to prove the correlation between the learner's characteristics and the method of delivering e-learning, specifically e-learning without support or e-learning with support activities. Based on the literature research described above, it is assumed that learners' individual characteristics (age, language competency and digital proficiency) affect learning-related stress factors and are related to their willingness to ask for support in order to complete their digital learning courses. Thus, I make a suggestion that characteristics influence their decision to take support for e-learning in general (H3) and specific type of support in particular (H4) – s. Fig 11. For example, one can guess that the older the learners are, the worse they language and digital skills are, the more likely they are to ask for support, when completing the e-learning course.

FIGURE 11: CONCEPTUAL MODEL FOR H3 AND H4 (OWN DESIGN)



The analysis is performed on the group of learners, who passed the test after more than 1 attempt (Sample 2). The number of training records is equal to 339.

The logistic regression is performed with the binary variable *support* (decided to take support as 1 and decided not to as 0 value) as dependent variable and age, language and digital proficiency as independent variables. Control variable is the *course_group*. I apply a logistic regression model using the *glm* (generalized linear model) function in R and test the model with and without controls (Table 12).

Code in R:

```
log_reg_h3_1 <- glm(support ~ age + language + digital_prof, data = elearning_h3, family = 'binomial')

log_reg_h3_2 <- glm(support ~ age + language + digital_prof + course_group, data = elearning_h3, family = 'binomial')
```

TABLE 12: RESULTS OF LOGISTIC REGRESSION FOR H3 FOR DV SUPPORT (N=339)

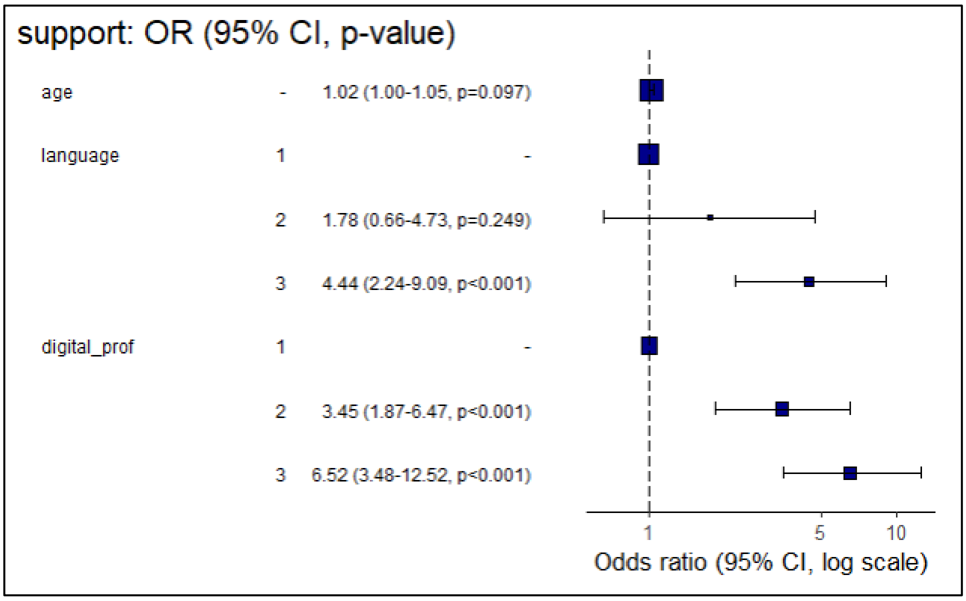
Log Reg. H3, DV suport, N=339	
	Dependent variable:
	support
age	0.023
	(0.014)
language2	0.596
	(0.500)
language3	1.524***
	(0.358)
digital_prof2	1.202***
	(0.324)
digital_prof3	1.803***
	(0.340)
course_groupGroup - Data	0.274
	(0.287)
course_groupGroup - Safety	0.012
	(0.581)
Constant	-2.997***
	(0.654)
Observations	339
Log Likelihood	-180.044
Akaike Inf. Crit.	376.088
Note:	*p<0.1; **p<0.05; ***p<0.01

Log Reg. H3, DV suport, N=339	
	Dependent variable:
	support
age	0.023*
	(0.014)
language2	0.576
	(0.499)
language3	1.491***
	(0.356)
digital_prof2	1.239***
	(0.316)
digital_prof3	1.875***
	(0.326)
Constant	-2.852***
	(0.631)
Observations	339
Log Likelihood	-180.541
Akaike Inf. Crit.	373.082
Note:	*p<0.1; **p<0.05; ***p<0.01

We can see that the model without controls has 3 points lower AIC alongside with approximately the same log likehood value. Additionally, the factor of age turns to be statistically significant in the model without controls, compared with the model with controls. To make sure, I perform a likelihood ratio test for differences in models, using the function *lrtest* in R. From the output we get the Chi-Squared test-statistic equal to 0.99 and related p-value 0.6. We can conclude that both full and nested models fit the data. The additional predictor variables in the full model though don't improve the model. Because of that we take the nested model. Thus, I select the model without controls and conclude that the course group does not affect the relation between the learner's characteristics and choosing support by a learner.

Analyzing the model and judging from the statistically significant coefficients, our model suggests that the age and digital proficiency of learners as well as language competency (level 3 only) influence the decision of learners to take the support. Exponentiating regression coefficients, it was found that, holding the other parameters constant, an increase of learner's age by 1 year is associated with the increase of 2.2% in the odds of asking for the support. The probability of asking for the support also increases in 4.44 times for language competency level 3 compared to level 1, in 3.45 times for learners with digital proficiency level 2 compared to level 1 and in 6.52 times with level 3 compared to level 1. Generally, we see a fit model with strong dependencies and can conclude that the decision to take support is strongly influenced by the learner's characteristics, especially their digital proficiency. The odds ratio values (confidence interval 95%) are visualized on the Figure 12.

FIGURE 12: ODDS RATIO PLOT FOR DV SUPPORT (N=339)



4.2.4 Hypothesis H4

According to the research model, described in the chapter 3, the variable "channel of knowledge transfer" is treated as binormal variable with the values 0 corresponding to "e-learning without support" and 1 "e-learning with support". The latter is operationalized as 2 binormal variables, representing 4 possible types of support, depending on if the support was delivered personally versus digitally or individually versus in a group (s. Chapter 2.5 for detailed description). Keeping in mind that the learners were able to choose any of these 4 support types (digital individual, digital group, personal individual or personal group), I would like to test, if the choice of a specific kind of supporting activities depend on the learner's characteristics and thus if the decision to select specific type of support is correlated with the learners' characteristics: age of learners, their language competency and digital proficiency (Fig. 11).

To test this hypothesis only the training records with support are taken from the Sample 2. The corresponding data frame contains 117 training records with the number of attempts, different from 1. Among them there are 36 records of the Group – Conduct, 76 records of the Group – Data and only 5 records of the Group – Safety. I exclude the records of the Group – Safety from the sample and the final size of the sample turns equal to 112 training records.

Split of the variable *support_method* is as follows:

1. digital individual – 21 records
2. personal individual – 29 records
3. digital group – 33 records
4. personal group – 29 records

Two additional dummy variables are introduced: binormal variable *digit_pers*, representing the choice of digital (1) versus personal (0) support, and variable *ind_group*, differentiating individual (1) versus group (0) support types.

I use logistic regression model to evaluate simultaneously the effect of three independent variables on a dependent variable. In our case dependent variable is a choice of support method (digital vs personal or individual versus group support type) with the following values:

- 1 – a learner has asked for and received their support through digital means of communication
- 0 – a learner has asked for and received their support on a personal meeting (in presence)

Code in R:

```
elearning_h4_1 <- glm(digit_pers ~ age + language + digital_prof + course_group, data = elearning_support_1, family = "binomial")
```

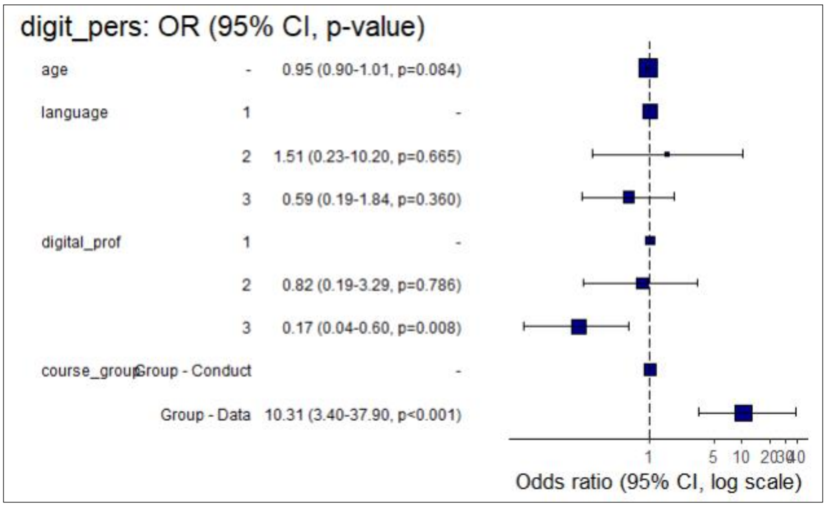
TABLE 13: RESULTS OF LOGISTIC REGRESSION FOR H4, DIGITAL VS PERSONAL SUPPORT (N=112, WITH SUPPORT)

	Dependent variable:
	digit_pers
age	-0.047*
	(0.027)
language2	0.411
	(0.949)
language3	-0.529
	(0.578)
digital_prof2	-0.195
	(0.718)
digital_prof3	-1.767***
	(0.664)
course_groupGroup - Data	2.334***
	(0.605)
Constant	1.305
	(1.290)
Observations	112
Log Likelihood	-55.017
Akaike Inf. Crit.	124.035
Note:	*p<0.1; **p<0.05; ***p<0.01

From the Table 13 we can conclude that both age and digital proficiency are statistically significant. The calculated p-value of the model is 4.496703e-08. It means that this model fits significantly better than the null model. These results would lead us to believe that digital proficiency, especially for the least proficient learners, and the age of learners significantly affect their choice between digital and personal type of support within the same course group.

Calculating the odds ratios, we can conclude that holding the other parameters constant, the odds of choosing digital over personal support type decreased by 5% for each additional year of age, and by 83% for learners with digital proficiency level 3 compared to level 1. All values of the odds ratio with the confidence interval 95% are demonstrated on the Figure 13.

FIGURE 13: ODDS RATIO PLOT FOR DV DIGITAL VS PERSONAL SUPPORT TYPE (N=112, WITH SUPPORT)



The next tested variable *ind_group* has the following values:

- 1 – a learner has asked for and received their support individually
- 0 – a learner has asked for and received their support in a group

Code in R:

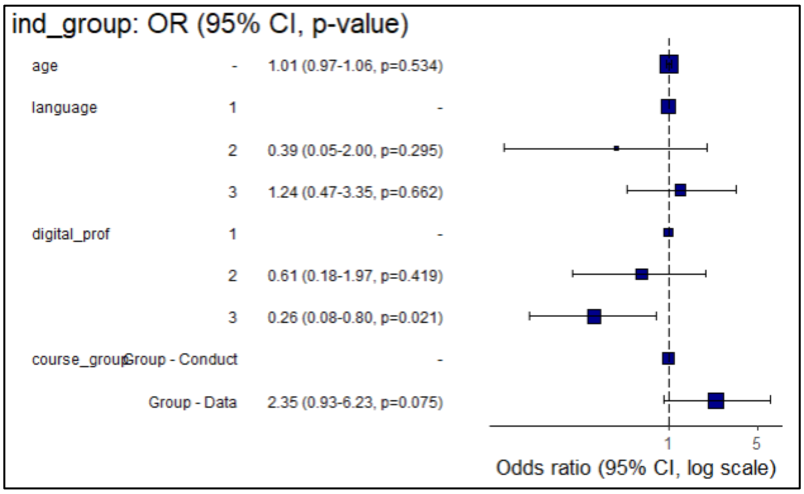
elearning_anova_h4_2 <- glm(ind_group ~ age + language + digital_prof + course_group, data = elearning_support_1, family = "binomial")

TABLE 14: RESULTS OF LOGISTIC REGRESSION INDIVIDUAL VS GROUP SUPPORT TYPE FOR H4 (N=112, WITH SUPPORT)

	Dependent variable:
	ind_group
age	0.014
	(0.022)
language2	-0.935
	(0.893)
language3	0.216
	(0.495)
digital_prof2	-0.490
	(0.606)
digital_prof3	-1.338**
	(0.578)
course_groupGroup - Data	0.855*
	(0.481)
Constant	-0.628
	(1.085)
Observations	112
Log Likelihood	-69.223
Akaike Inf. Crit.	152.446
Note:	*p<0.1; **p<0.05; ***p<0.01

The p-value of the model equals 0.0165, which means that the model is statistically significant. For the choice between individual and group support methods, digital proficiency level 3 turned out to be the only significant factor in the model (Table 14). The least proficient learners (level 3) are 74% more likely to choose support in a group rather than individually, compared to the most digitally proficient learners (level 1). It can be concluded that the learner's decision, either to take support individually or in a group with other learners, depends neither on language competency, nor on the age of learners, but solely on their digital proficiency. Figure 14 shows the values of the odds ratio with the confidence interval 95%.

FIGURE 14: ODDS RATIO PLOT FOR DV INDIVIDUAL VS GROUP SUPPORT (N=112, WITH SUPPORT)



Additionally, it could be interesting to check, which type of support lends the best learning outcomes in the form of the test score. For that, we apply a regression analysis with score as dependent variable and the two dummy variables *digit_pers* and *ind_group* as independent variables for the different support types. Additionally, we include the interaction of these two variables to check for their possible joint effect in our model and will also use the learners' characteristics age, language competency and digital proficiency as controls. In the Brant test for this model probability for *digital_prof2* and *digital_prof3* are close to 0.05, and we still can assume that the proportional odds assumption is not violated.

Code in R:

elearning_ h4_3 <- polr(score ~ digit_pers + ind_group + digit_pers:ind_group + age + language + digital_prof, data = elearning_support_1, Hess=TRUE)

The outcomes of this analysis are demonstrated on the Table 15.

In this model we can see that the variable *digit_pers* is statistically significant, whereas the variable *ind_group* is not. It can be concluded that the choice between digital and personal support types affects the test score, whereas between individual and group support – not.

We remember that our dependent variable *score*, where the level 1 refers to the best test score 100%. Thus, we can conclude that the learners, who took support in the digital form, are 77% more likely to score better at the test in comparison with the learners, who took support personally, keeping the other parameter constant.

The interaction of the variables *digit_pers* and *ind_group* is not significant. It means, that the latter variables are independent in this model.

TABLE 15: RESULTS OF ORDINAL REGRESSION FOR H4 WITH DV SCORE (N=112)

Ordinal Reg. H4, DV score, N=112	
	Dependent variable:
	score
digit_pers	-1.450**
	(0.607)
ind_group	-0.556
	(0.546)
age	0.034
	(0.021)
language2	-0.546
	(0.658)
language3	0.191
	(0.446)
digital_prof2	2.265***
	(0.679)
digital_prof3	1.414**
	(0.677)
digit_persTRUE:ind_group	1.189
	(0.815)
Observations	112
Note:	*p<0.1; **p<0.05; ***p<0.01

It can be concluded that considering the learning outcomes in the form of test scores, digital support methods prove to be more effective, comparing to the personal support methods.

5. Discussion

The testing conducted on the sample with the training records' data, provided a few insights related to the research question. The dependency of the learning outcomes of mandatory e-learning modules in the form of the test score and number of test attempts on such individual learners' characteristics as the age of learners, as well as their language competency and digital proficiency, with the existence of supporting activities, available for the learners in the organization, and with the type of this supporting activities, was confirmed using the ordinal logistic regression and logistic regression methods.

First of all, the broader term "learning outcome" was for the purpose of this research operationalized in three ways: as an ability to pass after-learning assessment from the first attempt, without any single repetition of the e-learning course, as the number of test attempts and as a test score of the obligatory assessment at the end of the course. According to Waugh (2019), such an control method is an optimal learning outcome verification for the mandatory compliance trainings. Referring to the widely recognized Kirkpatrick's model, such type of evaluation would describe the level two or the ability of a learner to understand the content, but not yet to apply it.

H1a	*The higher age of adult learners negatively affects the learning outcomes of e-learning*	confirmed

Both operationalizations of the learning outcomes show the causal relationship with the independent variable age of adult learners.

Ordinal logistic regression shows that the odds of passing the test at the very first attempt decrease by 2% for each additional year of age, as well as for passing the test by every next attempt.

As for checking across the test scores, the variable *age* turns out to be significant only for the group of learners, who failed to pass the test at the first attempt and thus were exposed to support option. For these so-called "weaker learners", the odds of having a test result less than 100% increased by approximately 2% for each additional year of age.

It appears that for the "good learners", who were able to pass the test at the first attempt, the age factor did not play an important role and the regression results turned to be insignificant.

H1b	*The higher language competency of learners positively affects the learning outcomes of e-learning*	rejected

Generally, the ordinal categorical variable *language* competency looked weak in most of the regression models. It could be suggested that the definition of it, based on the data about learners' citizenship and availability of language certificates, received from HR department, was not accurate enough. Checking the cross-tabs in the Appendix 3 one can notice, that the language competency level 2 group is the smallest and contains only 36 learning records. It could have affected the regression results for this group.

It could also be suggested that the quality and the level of visualization of e-learning courses was high enough, what helped the learners to understand the context non-verbally.

However, in case of analyzing the ability to pass the test at the first attempt, the variable *language3* (the worst language competency) yield significant result. The odds of passing the test at the first attempt decreased by 66% for the learners with level 3 compared to level 1 of language competency.

H1c	*The higher digital proficiency of learners positively affects the learning outcomes of e-learning*	confirmed

The results of all the regression models in this study reveal, that the effect of digital proficiency on all dependent variables in question is the highest, compared to other two investigated learner's characteristics.

Holding the other parameters constant, the odds of passing the test at the first attempt decreased by 75% for learners with digital proficiency level 2 compared to level 1 and by 90% with level 3 compared to level 1.

Specifically, for the test *score*, the results prove that in case of improving the digital proficiency of learners from level 3 to level 1, one could expect the increase of test score in 2.7 times and in 1.9 times, moving from level 2 to level 1.

Looking at the number of test *attempts*, we can notice that the results here are not as straightforward. It was initially suggested that the higher digital proficiency is, the less test attempts is needed to pass the test at the end of the training. Nevertheless, with the help of cross tabulation we have observed that the learners with the highest and lowest digital proficiency were passing the test with a smaller number of attempts, comparing to the group with the medium level 2. The results of the ordinal logistic regression confirm it and show that the odds of having more test attempts increase by 58% for the learners with the digital proficiency level 2, compared to level 1. An impact of the availability of support was suggested to play an important role in case of less digitally affine learners.

Looking closer at the sample, containing only support records (n=112), it was concluded that mostly the learners with the worst digital proficiency (level 3) were not confident enough to attempt a digital test themselves and waited for supporting sessions, whereas the learners with a medium level 2 of digital proficiency were inclined to have more test attempts without support.

Thus, it can be suggested that they have higher self-efficacy, comparing to the level 3 group, and tend to perform more test attempts themselves, waiting for their digital group support appointment.

Testing the interdependency of the test *score* and learners' characteristics, generally, the results of the ordinal logistic regression in my study prove the validity of tested models both for the samples with only one test attempt and with more than one test attempt.

Nevertheless, it can be noticed that the influence of age and digital proficiency level is much higher for the group of learners, who failed by the first attempt and had to repeat the course at least once. This fact suggests that there could be another factor, influencing the leaners' self-efficacy in the group of learners with more than one test attempt. In other words, for those who could easily pass the test at the first attempt, it did not matter much, how old they were, because some other factor was more important, but for those who experienced a failure at least once, the fact of failure showed the absence (or lower influence) of this unaccounted factor, but a proven dependency between the age and the test result.

Taking into consideration the findings, related to the number of test attempts, it can be suggested that this factor could be the availability of support opportunity, which is obviously not that important for the "good learners", able to pass the test after the very first attempt, but getting more important with the decreasing of the digital proficiency of learners.

The link between the existence of support activities and the learning outcomes in form of test score, was analyzed further in my thesis.

The results of ordinal logistic regression, applied in H2, prove that the learners who took support option, scored significantly better in the training tests. Thus, the odds of having the test result worse that 100% decreased by 35% for the learners who took support.

H2	*Support activities improve the learning outcomes of e-learning in the form of test score*	confirmed

The results of logistic regression, used to test H3, reveal the increase of probability to ask for the support in case of older learners and the learners with lower language competency and digital proficiency, although again the results for language competency seemed less convincing ($p > 0.5$ for *language2*). Apart from the general concerns, related to the definition of the variable *language*, the size of group *language2* in the sample for H3 was pretty small (22 observations, compared to 263 observations for *language1* and 54 observations for *language3*).

Nevertheless, generally the regression model confirms as well the dependency between the language level of learners and their decision to ask for support. Holding the other parameters constant, an increase of learner's age by 1 year is associated with the increase of 2.2% in the odds of asking for the support. The probability of asking for the support also increases in 4.44 times for language competency level 3 compared to level 1, in 3.45 times for learners with digital proficiency level 2 compared to level 1 and in 6.52 times with level 3 compared to level 1. We can see the dependencies between the learners' characteristics and their intention to take support are even stronger the in case of learning outcomes.

H3a	*The higher age of adult learners negatively affects their decision to take support for e-learning*	confirmed
H3b	*The higher language competency of learners positively affects their decision to take support for e-learning*	confirmed
H3c	*The higher digital proficiency of learners positively affects their decision to take support for e-learning*	confirmed

The correlation with the learner's characteristics has similar logic, compared to the previous hypotheses: the "weaker" is an individual characteristic, the lower is the self-efficacy, the higher need for support have the learners.

More insights related to the specific preferred type of support were received, when testing the hypothesis H4. The age of learners did not seem to be significant, when choosing a specific type of support.

It appeared that digital proficiency was a determining factor both in the case, when the learners had to decide between group and individual type of support and between the support through digital means of communication and face-to-face.

With the help of logit regression, we proved that the least proficient learners (level 3) are 74% are more likely to choose support in a group rather than individually, compared to the most digitally proficient learners (level 1). It can be concluded that the learner's decision, either to take support individually or in a group with other learners, depends neither on language competency, nor on the age of learners, but solely on their digital proficiency.

Predictably, it was concluded that digital proficiency, especially for the least proficient learners, significantly affected their choice between digital and personal type of support within the same course group. On the other hand, the older learners were more likely to choose face-to-face supporting activities, the odds of it increased by 5% for each additional year of age.

It can be emphasized that the testing does not confirm the interdependency of age and digital proficiency of learners in the treated sample.

H4	*Learner's characteristics influence their decision to take specific type of support*	confirmed

Coming back to our research question, special attention was paid to the influence of the choice of specific support method on the learning outcomes.

Tested ordinal regression model revealed that the choice between digital and personal support types affects the test score, whereas between individual and group support – not.

It is remarkable that the learners, who took support in the digital form, are 77% more likely to score better at the test in comparison with the learners, who took support personally, keeping the other parameters constant.

In was discovered that all the learners with the worst digital proficiency in our sample chose the "personal group" type of support. It indicates the necessity to treat this group of learners with low self-efficacy separately when planning the learning setup, and provide them the possibility to decrease their learning-related anxiety in face-to-face group support sessions.

Finally, the findings of this study highlight the importance of support activities in the implementing effective digital learning strategy in organizations. The overall results prove that the focus of these support activities should be on increasing the digital proficiency or comfort level with technology of learners as a factor, which plays the most important role in the learning outcomes of e-learning.

6. Conclusion

The assessment of the examined hypotheses served to answer the research question of this thesis:

Do the learners' characteristics and support activities influence individual learning outcomes during e-learning?

The general conclusion could be that both the learners' individual characteristics, such as age and digital proficiency as well as the availability of supporting activities in a blended learning setting influences the learning outcomes of obligatory compliance e-learning modules.

6.1. Theoretical Implications

First of all, it should be mentioned that the digital proficiency of learners was proven to be a key factor, playing the most prominent role in successful passing the control tests, as well as in passing the test from the first attempt, by influencing the learners' self-efficacy in case of learning digitally. It is important, that the link between digital proficiency of learners and their level of confidence in case of digital training setup directly affects the number of test attempts, taken by the learners before asking for support, as well as the training method they prefer. These findings are in line with the latest research, linking lower computer skills to the decreased self-efficacy of learners and increased stress, when learning from digital courses and thus to worse learning outcomes (Hardaker and Smith, 2002; Sawang, Newton and Jamieson, 2013; Zhonggen, 2015; Naresh, Sree Reddy and Pricilda, 2016).

With regards to the age of learners, my study confirms the previous research, e.g., by McEnrue (1989), Horn and Noll (1994), who investigated the relation between age and employees' ability and training motivation in general and Martocchio and Webster (1992), who narrowed their focus to digital learning in particular. It can be concluded that for the adult learners the increasing in age leads to the declining of ability to pass the training test at the first attempt, increasing the total number of attempts required to pass the test and also negatively affects the training test scores. The latter is valid only for the group of learners, who fail to pass the test at the first attempt.

Generally, the support activities seem to play a very important role in the success of digital learning. These findings confirm the previous studies (Sawang, Newton and Jamieson, 2013; Sivankalai, 2021; Suzianti and Paramadini, 2021), proving the importance of personal interaction of the instructor or manager with a learner in order to create "positive training atmosphere" and increase "pretratining motivation". Thus, interacting with the instructor, the learners believe to feel safer and more self-confident to start learning digitally, and they would generally rather choose support than not.

6.2. Managerial Implications

From the business perspective, it could be important for the organizations to build a link between the learner's characteristics, available in the data of companies' HR databases and Learning Management Systems, and the learning efficiency. Special interest arises in the question of self-paced digital learning modules (e-learning), highly demanded by the pandemics-affected companies worldwide and requiring sufficient investments for the implementation (Deloitte, 2021).

The results of these study as well as a following empirical study of the factors, affecting the efficiency of digital learning, could contribute to building an effective digital learning strategy of organizations by showing the way to create effective ways of digital learning implementation.

Specifically, knowing the influence of learners' characteristics on the ability to effectively learn digitally, the resources of the organizations can be planned more effectively. For example, the learners with medium and high digital proficiency should be offered digital support options, specific for each of these groups. It could be expected that the older learners would need more time for test attempts and could have lower test scores.

Important outcome of my thesis is that the learner's demand for support depends on all the three analyzed individual characteristics. So, it can be well predicted, who needs the support the most, as well as which exactly types of support could be the most effective for different groups of learners.

Finally, I believe, that there could be some field for the future research of the most optimal blended learning settings for the different groups of learners, based on their characteristics and organizational environment.

6.3. Limitations and Directions for Future Research

First of all, it should be mentioned that this thesis does not take into consideration levels 3 and 4 of Kirkpatrick's model, i.e., how obtained by learners' knowledge is used and how it impacts the organization. This could also be the direction of the future research.

There could be some other, not considered factors, influencing the learning outcomes. For example, Holton III (2005) stresses out the importance of transfer climate for the knowledge transfer in the organization. Some specific issues could be influencing this parameter in the different departments and sites, where the learners are employed. Such a climate can be linked to the person of a manager (Facteau et al., 1995), which was not controlled for in this research.

It could be also suggested that the content topic specifics and the difficulty of specific online learning modules can be a factor, which also affected the learning outcomes and need for support by learners. Among other scholars, Holton III (2005) in his model of evaluating the efficiency of the transfer of learning to individual performance argues that learning design has sufficient importance. To control for this influence in my research I grouped 23 learning modules into 3 groups and included these groups as control variables. It could still be the case, that the grouping, made based on expert opinion, was not done in the optimal way.

Certain limitations are caused by the subjectivity of the definition for such learners' characteristics as digital proficiency and language competency. The first was defined mostly based on the job roles of learners and some expert opinion of HR specialists, what allows some degree of subjectivity. The latter was determined by the data about learners' citizenship and availability of language certificates, and is of course not exactly accurate. We could see that the number of training records for language2 group was not more than 36 records in all samples. It has certainly affected the testing results.

As mentioned in Sawang, Newton and Jamieson (2013) the previous experience with e-learning could have played an important role in the learners' efficiency. Unfortunately, we do not have data, which learners had previous experience with e-learning outside of the organization.

All the factors, mentioned above, limit the accuracy of present work and could be the directions of the future study.

For the future research it would be interesting to expand the focus from just identifying the fact of learners' characteristics influencing the learning outcomes to looking deeper into the reasons, why does this influence occur.

For example, it seems to be beneficial to investigate the possible influence of learning characteristics on the self-efficacy of learners, which can be taken into the model as a predictor.

The further learning characteristics, like a learner's job role or availability of manager's and team's support could also be added to get a clearer picture of factors, influencing individual learning outcomes.

The learning design can also be investigated more precisely in order to find the optimal blend of learning activities, allowing different groups of learners to perform at their best. Generally, it seems that the rapid development of different sorts of blended learning activities requires a continuous attention of researches, working together with business and HR representatives, in order to make this development as efficient as possible.

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8. Appendix

Appendix 1: Total number of learning records derived from LMS for e-learning courses and groups

Course Name/ Course Group	Number of learning records*
Group – Conduct (total):	**470**
Code of Conduct	422
Frontline Code of Conduct	46
Safeguarding Children and Vulnerable Adults	2
Group – Data (total):	**1 034**
Data Protection	497
Information Security	535
Data Management - basics	2
Group – Finance (total):	**66**
Corporate Finance - Leases	29
Introduction to Finance	35
Top 10 Finance Controls	2
Group – Safety (total):	**651**
Driver Safety	9
Health, Safety and Environment	35
Last Minute Risk Assessment	1
Office Safety	346
Safety Rules - Confined Space Entry	21
Safety Rules - Driving Safety	27
Safety Rules - Electrical Safety	30
Safety Rules - Energy Isolation	25
Safety Rules - Housekeeping	29
Safety Rules - Manual Handling	25
Safety Rules - Permit to Work	23
Safety Rules - Stopping Unsafe Work	28
Safety Rules - Working At Heights	24
Safety Rules - Working With Chemicals	28
Total number of learning records:	**2 221**

* The number of records includes the total training records per course before removal of different course records for same learners

Appendix 2: Overview of the Variables

Variable	Type of the variable	Description
age	numeric	Age of a learner in years
language	factor	Illustrates language competency of a learner: 1 – native speaker or level C1 2 – level A2-B2 3 – level A1
digital_prof	factor	Illustrates digital proficiency of a learner: 1 – high digital proficiency (all office roles, second-line managers in operations and technical specialists). These learners use computer over 50 per cent of their working time. 2 – medium digital proficiency (operations managers, specialist in operations, apprentice) with computer use below 50 per cent of their working time. 3 – low digital proficiency (front line jobs, team leader operation), who do not use computer at work.
course_name	factor	Name of the e-learning module. There is only one e-learning record per learner for every e-learning module.
course_group	factor	Group of e-learning modules with similar topic: Group – Conduct, Group – Safety, Group – Data
attempts	factor	Number of attempts before a learner achieved 80 % test score on the final test. Learners have unlimited number of attempts and they have to repeat the whole module before they achieve the needed score.
first_attempt	binormal	1 – passed at 1 attempt 0 – number of attempts upon completion are more than 1
score	factor	1 – high test score (100%) 2 – medium test score (more than 80%, but less than 100%) 3 – low test score (80%)
support	binormal	1 – a learner has asked for and received support after failing by their first attempt to compete the test 0 – a learner has neither asked nor received the support
digit_pers	binormal	1 – a learner has asked for and received their support through digital means of communication 0 – a learner has asked for and received their support on a personal meeting (in presence)
ind_group	binormal	1 – a learner has asked for and received their support individually 0 – a learner has asked for and received their support in a group

Appendix 3: Cross-Tabulations (n=640)

Cross-Tabulation for Digital Proficiency in Different Course Groups

course_group	*digital_prof* 1	2	3	***Total***
Group - Conduct	129 61.4 %	52 24.8 %	29 13.8 %	210 100 %
Group - Data	174 47.9 %	97 26.7 %	92 25.3 %	363 100 %
Group - Safety	46 68.7 %	21 31.3 %	0 0 %	67 100 %
Total	349 54.5 %	170 26.6 %	121 18.9 %	640 100 %

χ^2=31.528 · df=4 · Cramer's V=0.157 · p=0.000

Cross-Tabulation for Language Competency in Different Course Groups

course_group	*language* 1	2	3	***Total***
Group - Conduct	163 77.6 %	13 6.2 %	34 16.2 %	210 100 %
Group - Data	291 80.2 %	20 5.5 %	52 14.3 %	363 100 %
Group - Safety	60 89.6 %	3 4.5 %	4 6 %	67 100 %
Total	514 80.3 %	36 5.6 %	90 14.1 %	640 100 %

χ^2=5.002 · df=4 · Cramer's V=0.063 · Fisher's p=0.269

Cross-Tabulation for Age Groups in Different Course Groups

course_group	*age_group* 1	2	3	***Total***
Group - Conduct	53 25.2 %	107 51 %	50 23.8 %	210 100 %
Group - Data	91 25.1 %	183 50.4 %	89 24.5 %	363 100 %
Group - Safety	16 23.9 %	29 43.3 %	22 32.8 %	67 100 %
Total	160 25 %	319 49.8 %	161 25.2 %	640 100 %

χ^2=2.474 · df=4 · Cramer's V=0.044 · p=0.649

age_group=1 contains the values of *age* up to 33.59, *age_group*=2 - from 33.57 to 49.07, *age_group*=3 - above 49.07. Division according to Q1 and Q3 of the variable *age*.

Cross-Tabulation for Support in Different Course Groups

course_group	*support* 0	1	***Total***
Group - Conduct	174 82.9 %	36 17.1 %	210 100 %
Group - Data	287 79.1 %	76 20.9 %	363 100 %
Group - Safety	62 92.5 %	5 7.5 %	67 100 %
Total	523 81.7 %	117 18.3 %	640 100 %

χ^2=7.145 · df=2 · Cramer's V=0.106 · p=0.028

Cross-Tabulation for Digital Proficiency vs Score

digital_prof	*score* 1	2	3	***Total***
1	207 59.3 %	52 14.9 %	90 25.8 %	349 100 %
2	42 24.7 %	75 44.1 %	53 31.2 %	170 100 %
3	24 19.8 %	54 44.6 %	43 35.5 %	121 100 %
Total	273 42.7 %	181 28.3 %	186 29.1 %	640 100 %

χ^2=102.213 · *df*=4 · *Cramer's V*=0.283 · *p*=0.000

Cross-Tabulation for Language vs Score

language	*score* 1	2	3	***Total***
1	225 43.8 %	138 26.8 %	151 29.4 %	514 100 %
2	14 38.9 %	13 36.1 %	9 25 %	36 100 %
3	34 37.8 %	30 33.3 %	26 28.9 %	90 100 %
Total	273 42.7 %	181 28.3 %	186 29.1 %	640 100 %

χ^2=2.961 · *df*=4 · *Cramer's V*=0.048 · *p*=0.564

Cross-Tabulation for Age Group vs Score

age_group	*score* 1	2	3	***Total***
1	77 48.1 %	41 25.6 %	42 26.2 %	160 100 %
2	136 42.6 %	88 27.6 %	95 29.8 %	319 100 %
3	60 37.3 %	52 32.3 %	49 30.4 %	161 100 %
Total	273 42.7 %	181 28.3 %	186 29.1 %	640 100 %

χ^2=4.187 · *df*=4 · *Cramer's V*=0.057 · *p*=0.381

age_group=1 contains the values of *age* up to 33.59, *age_group*=2 - from 33.57 to 49.07, *age_group*=3 - above 49.07. Division according to Q1 and Q3 of the variable *age*.

Cross-Tabulation for Course Group vs Score

course_group	*score* 1	2	3	***Total***
Group - Conduct	131 62.4 %	68 32.4 %	11 5.2 %	210 100 %
Group - Data	122 33.6 %	75 20.7 %	166 45.7 %	363 100 %
Group - Safety	20 29.9 %	38 56.7 %	9 13.4 %	67 100 %
Total	273 42.7 %	181 28.3 %	186 29.1 %	640 100 %

χ^2=137.896 · *df*=4 · *Cramer's V*=0.328 · *p*=0.000

Appendix 4: Abstract

A. Abstract in English

In the information economy of today, only employees provided with the up-to-date knowledge of relevant data and processes can help their enterprise to compete effectively. E-learning is an effective tool for just-in-time information access, especially valuable for enterprises with global operations. (Morrison, 2003). Effective knowledge transfer through e-learning can depend on different factors, including methodological, organizational and technical support of learners (Drozdova and Guseva, 2017), and learner's individual characteristics, such as their age, language competency and digital proficiency (Martocchio and Webster, 1992; Colquitt, LePine and Noe, 2000; Hardaker and Smith, 2002; Sawang, Newton and Jamieson, 2013). This thesis contains the analysis of the impact of learners' individual characteristics on the learning outcome as well as the effect, which has the existence and type of instructor-led supporting activities. The data sample, derived from the learning management system of the Austrian subsidiary of multinational company, contains 640 training records, registered in the period of 2020-2021. The results demonstrate that the learners' individual characteristics, such as age and digital proficiency, as well as the availability of supporting activities in a blended learning setting, influences the learning outcomes of obligatory compliance e-learning in the form of post-training knowledge assessment. Furthermore, the learner's digital proficiency appeared to be the main determining factor of learning outcomes for compliance e-learning. The suggestions of other possible predictors were made and the direction of a future research identified.

B. Abstract in German

In der heutigen Informationswirtschaft können nur Mitarbeitende, die über aktuelles Wissen über relevante Daten und Prozesse verfügen, ihrem Unternehmen helfen, sich im Wettbewerb durchzusetzen. Ein E-Learning ist ein effektives Instrument für den zeitnahen Zugriff auf Informationen, das besonders für global agierende Unternehmen wertvoll ist. (Morrison, 2003). Ein effektiver Wissenstransfer durch E-Learning kann von verschiedenen Faktoren abhängen, z. B. von der methodischen, organisatorischen und technischen Unterstützung der Lernenden (Drozdova und Guseva, 2017) und von den individuellen Merkmalen der Lernenden, wie z. B. ihrem Alter, ihrer Sprachkompetenz und ihren digitalen Kenntnissen (Martocchio und Webster, 1992; Colquitt, LePine und Noe, 2000; Hardaker und Smith, 2002; Sawang, Newton und Jamieson, 2013). In dieser Arbeit wird untersucht, wie sich die individuellen Merkmale der Lernenden auf die Lernergebnisse auswirken und welche Auswirkungen die Existenz und die Art der von dem/der Trainer:in durchgeführten unterstützenden Aktivitäten haben. Die Stichprobe, die aus dem Lernmanagementsystem der österreichischen Tochtergesellschaft eines multinationalen Unternehmens stammt, umfasst 640 Schulungsdatensätze, die im Zeitraum von 2020 bis 2021 dokumentiert wurden. Die Ergebnisse zeigen, dass die individuellen Merkmale der Lernenden, wie z. B. Alter und digitale Fähigkeiten, sowie die Verfügbarkeit von unterstützenden Aktivitäten in einer Blended-Learning-Umgebung die Lernergebnisse des verpflichtenden E-Learnings in Form einer Wissensüberprüfung nach der Schulung beeinflussen. Darüber hinaus scheint die digitale Kompetenz der Lernenden der wichtigste Faktor zu sein, der die Lernergebnisse beim E-Learning bestimmt. Es wurden Vorschläge für weitere mögliche Faktoren gemacht und die Richtung einer zukünftigen Forschung aufgezeigt.