Transforming Learning & Development:

The Impact of Artificial Intelligence and Automation on Employee Motivation to learn

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Abstract

Title: Transforming Learning & Development: The Impact of Artificial Intelligence and Automation on Employee Motivation to learn

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Technological advancements have transformed employee learning and development (L&D) from one-size-fits-all approaches to personalized initiatives. Given AI's potential to learn and adapt to individuals' demands, researchers and practitioners have started investigating AI applications in L&D. However, whether employees prefer AI-guided learning and whether it actually drives motivation to learn remains an empirical question. Thus, this research aims to investigate the impact of AI-guided L&D compared to simple automation-based L&D on employee motivation to learn, drawing on the Self-determination Theory (SDT) and the Unified Theory of Acceptance and Use of Technology (UTAUT). The proposed model was tested using a PLS-SEM analysis with 144 participants in an experimental survey. The results revealed that AI in L&D increases motivation to learn more than simple automation. However, this effect is fully mediated by the increase in perceived competence due to AI, emphasizing the importance of providing customized trainings tailored to employees' learning styles and skills, along with consistent feedback, to foster perceived competence. Furthermore, the study demonstrates that motivation to learn significantly predicts individuals' behavioural intention to use a L&D system. Specifically, AI-guided L&D, promoting competence, generates higher motivation to learn, leading to increased use intentions. Thus, the study highlights that AI in employee L&D drives autonomous motivation through self-determination surpassing simple automation-based approaches. These findings provide valuable implications for organizations and practitioners seeking to foster employee motivation and technology acceptance through new L&D solutions, suggesting that investing in AI could be beneficial.

Keywords: Artificial Intelligence, Simple Automation, Learning & Development, Employee Motivation, SDT, Technology Acceptance, UTAUT

Sumário

Título: Transformar a aprendizagem e o desenvolvimento: O impacto da Inteligência artificial e da automatização na motivação dos trabalhadores para aprender

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Os avanços tecnológicos revolucionaram a aprendizagem e desenvolvimento dos trabalhadores (L&D), passando de abordagens genéricas para personalizadas. Com o potencial da IA em aprender e adaptar-se às necessidades individuais, os investigadores têm-se dedicado a pesquisar potenciais aplicações em L&D. No entanto, ainda é uma questão empírica se os funcionários preferem a aprendizagem orientada por IA e se esta gera maior motivação para aprender. Esta investigação visa investigar o impacto da L&D orientada por IA em comparação com a L&D baseada em automação simples na motivação dos funcionários para aprender, com base na teoria da autodeterminação (SDT) e na teoria unificada de aceitação e uso de tecnologia (UTAUT). O modelo proposto foi testado com 144 participantes através de uma experiência utilizando análise PLS-SEM. Os resultados mostraram que a IA em L&D aumenta a motivação dos trabalhadores mais do que a automação simples. No entanto, este efeito é mediado pelo aumento da competência percebida devido à IA, enfatizando a importância de treino personalizado adaptado aos estilos e habilidades de aprendizagem dos trabalhadores, com feedback consistente, para promover a competência. A motivação para aprender demonstrou ser um preditor significativo da intenção comportamental dos indivíduos de usar um sistema de L&D. Especificamente, a L&D orientada por IA, ao promover a competência, gera maior motivação para aprender, resultando em maiores intenções de uso. Estes resultados têm implicações valiosas para organizações e profissionais que buscam promover a motivação dos trabalhadores e a aceitação de tecnologia em soluções de L&D, indicando os benefícios do investimento em IA.

Palavras-chave: Inteligência Artificial, Automatização Simples, Aprendizagem e Desenvolvimento, Motivação dos Empregados, SDT, Aceitação da Tecnologia, UTAUT

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Glossary

&	And
A	Autonomy
AI	Artificial Intelligence
ß	Beta-Coefficient (Regression Coefficient)
BI	Behavioural Intention to use
C	Competence
DV	Dependent variable
EE	Effort Expectancy
H1	Hypothesis 1 (2-10 respectively)
HR(M)	Human Resource (Management)
IT	Information Technology
IV	Independent variable
IPA	Intelligent Process Automation
L&D	Learning & Development
LMS	Learning Management System
M	Sample mean
ML	Machine Learning
MTL	Motivation to learn
N	Total number of cases
p	p-value
PE	Performance Expectancy
PLS-SEM	Partial least squares structural equation modelling
R	Relatedness
R^2	R-squared; coefficient of determination; measure of variance explained
RPA	Robotic Process Automation
SD	Standard Deviation
SDT	Self-determination Theory
SI	Social Influence
t	t-statistic (t-value)
TAM	Technology Acceptance Model
TEL	Technology-enhanced learning
UTAUT	Unified Theory of Acceptance and Use of Technology

1 Introduction

1.1 Topic presentation

With the release of ChatGPT by Open AI in the end of 2022, a new powerful AI tool was made publicly available and received great attention by (social) media and press. As its capabilities range from simply answering questions to telling stories and writing complex codes, AI's power and its potential to overtake "knowledge work" is showcased. Thus, due to continuous AI improvements, some jobs currently undertaken by humans will be reserved for automation, whereas, at the same time, new jobs and tasks will be created by AI (Agrawal et al., 2022; Dumesnil, 2023).

This idea is also supported by Anthony et al. (2023), who argue that human work will not be replaced by AI completely, but that rather the nature of work will change, meaning that new roles and tasks will be formed, and existing ones will be transformed. Thus, by positioning AI as an actor within a work system, technology developers, organizations and employees need to collaborate to enable a successful AI integration (Anthony et al., 2023). In order to successfully manage the transition to this AI-based future way of working, companies are striving to attract and retain the most talented employees (Adamson, 2022).

As career development is a significant motivational factor for employees to stay with the organization, providing effective training and development opportunities is thus essential (Chen, 2014). Indeed, when utilized efficiently, employee training bears the potential to enhance employees' job satisfaction and organizational engagement levels, simultaneously expanding their knowledge, skills, and capabilities (Chen, 2014).

Thus, with skilled and motivated employees as key intangible assets within an organization, who greatly contribute to organizations' innovativeness and business continuity, workplace learning and development (L&D) is becoming an important area for business success (Naim, 2023).

In recent years however, employee training and development has experienced a significant change, from "mass upskilling" of multiple individuals to customized, on-the-go training needs for each employee (Maity, 2019; Naim, 2023). The major trends can be summarized by the so-called **SIP Model**, which states that learners simultaneously are seeking a seamless, intuitive, and personalized learning experience (Maity, 2019): **(1) Seamless** – With new market entrants and organizational growth, a solid knowledge management system is needed, which enables every employee to access both tacit and codified knowledge. **(2) Intuitive** – As L&D nowadays is moving away from instructor-led in-classroom settings to online trainings accessible via mobile screens, intuition and adaptability of the modes play a major role. **(3) Personalized** – Whereas previously L&D programs were broadcasted to an array of employees, today L&D is shifting to an individualization of training initiatives based on employees' learning styles (Maity, 2019).

According to Alamri et al. (2020) personalized learning is an educational approach which provides learners with various learning options and adjusts the learning material to suit individual learning needs, interests, goals, and past experiences, and thus aims at improving learners' knowledge and skills and promoting psychological need satisfaction and intrinsic motivation.

As designing and scheduling such individual need-based training initiatives is time-consuming and requires high resource investments from organizations, AI-based applications take on an important role in supporting HR management, by cutting these lengthy processes and providing several opportunities to satisfy employees' training demands. - Be it the identification of learners' characteristics, the matching of employees' skills with appropriate training programs and learning modules, the automated tracking of individual learning progress or the on-demand feedback - AI is capable of doing all of it (Chen, 2022; Maity, 2019).

Given these recent developments concerning new technological capabilities and the ongoing race for the best talents, firms in general, and HR departments in particular, are required to adopt to work with AI, in order to stay competitive and to attract and motivate the best employees (Naim, 2023).

But what will be employees' reaction to this? At the end of the day, if organizations depend on this critical mass of employees and are willing to invest in the learning and development of its employees, it is crucial to know if it works well for them and keeps them motivated to continue learning. While theoretically it makes sense, it is an empirical question. Of particular importance here is the matter of motivation and in particular employees' motivation to learn. As previously noted, motivation is a key construct to keep employees engaged and satisfied within a working context (Chen, 2014). As such, motivation has been largely studied and the theories on how it works abound (Kanfer & Chen, 2016).

One theory, the Self-determination Theory (SDT) proposes that employees should experience feelings of autonomy within their work environment, which as a result then potentially not only leads to higher levels of employee satisfaction and well-being, but also benefits organizational effectiveness (Deci et al., 2017). Thus, employees, who are autonomously motivated, participate fully willing, voluntary, and self-directed in an (learning) activity (Deci et al., 2017). Therefore, self-determination can be achieved, when employees recognise their strengths and weaknesses and develop a strong belief in their own capabilities and effectiveness (Alamri et al., 2020). Linking both the SDT and AI-guided learning seems now only natural, given AI's capabilities of creating personalized learning experiences, which promote employees' striving for satisfying their three psychological needs (e.g., competence, autonomy, and relatedness) upon which self-determination builds.

But what does it benefit an organization, if its employees are fully motivated to learn, but not willing to use a newly implemented AI-guided learning and development (L&D) system, because they are reluctant to accept it? It therefore also makes sense to link AI-guided learning to a technology acceptance model, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), which provides a holistic view on individuals' usage intentions of new information technology (Venkatesh et al., 2003).

In my dissertation I will therefore analyse Artificial Intelligence (AI)-guided and simple automation-based employee learning and development and its impacts on employees' motivation to learn by referring to the Self-determination Theory and the Unified Theory of Acceptance and Use of Technology. My core hypothesis is that the use of AI in employee learning and development drives autonomous motivation through self-determination more than simple automation-based learning and development. I argue that given the potential of AI-guided L&D concerning personalized adaptive learning experiences, employees' needs for autonomy, competence, and relatedness (e.g. self-determination) become more satisfied and thus their motivation to learn as well as their intention to actually engage with such a L&D system is increased.

1.2 Problem Statement & Research Questions

Various studies have highlighted learners' motivation as an important factor to consider in training and development environments (Kashive et al., 2021; Wang et al., 2019) and different motivation types have been analysed (Colquitt et al., 2000). One specific type of motivation, "motivation to learn" defined by Colquitt et al. (2000, p. 681) as "the desire on the part of trainees to learn the training material", is of particular importance when assessing learners' willingness to broaden their knowledge and applying it within their work context (Hicks, 1983). Over the years, scholars have developed new theories, taking into consideration the arising technology-enhanced training methods and found that some of the ancestors of motivation to learn are influenced by the training delivery method (Chung et al., 2022). By applying the Self-determination Theory (SDT), which originated from Deci (1971) and is to date still one of the most thorough views on people's motivation (Van den Broeck et al., 2021) scholars were able to find significant relationships between online learning and individuals' three psychological needs (e.g., autonomy, competence, and relatedness) (Alamri et al., 2020; Hsu, 2021).

Furthermore, researchers have attempted to investigate the acceptance of new information technology over the past few decades (Davis, 1989). This led to the insight that individuals' behavioural intention to continuously use a new information system is an essential factor for it being successful (Venkatesh et al., 2003). Thus, previous studies also aimed at developing frameworks for dealing with the connections between the Technology Acceptance Model (TAM) and the Self-determination Theory (SDT), the majority of which have discovered favourable connections (Roca & Gagné, 2008).

In a similar manner, researchers have also started to investigate the relationships between the Unified Theory of Acceptance and Use of Technology (UTAUT) and the SDT in information and communication technology, and positive relationships among the two theories have been verified (Lee et al., 2015). Compared to the TAM, the UTAUT represents a more recent model that concentrates on the intention to use new information technology (IT) in a work setting and provides a holistic view of user acceptance by combining eight widely recognized technology acceptance models (Venkatesh et al., 2003). First introduced by Venkatesh et al. (2003), it has since then been successfully applied in various contexts, such as e-learning (Yoo et al., 2012), web-based learning (Chiu & Wang, 2008) and online learning (Batucan et al., 2022) among others, and was lately also used to investigate usage intentions for AI-related technology (Andrews et al., 2021). Scholars have also explored the positive relationship between learners' self-determination and their acceptance in massive open online courses (LMOOCs) built on the UTAUT model and found all three psychological needs (autonomy, competence, and relatedness) to be significant for learners' motivation and thus highlighted that learners' self-determination positively impacts learners' use intentions (Hsu, 2021).

Most of the studies conducted, however have focused on technology adoption in online language learning (MOOCs) (Hsu, 2021) or learning in general, with participants mostly being students. However, few scholars have investigated the relationships between the SDT and the UTAUT in work settings (Haque et al., 2018; Mabaso, 2020). Furthermore, most of the studies focused on either simple (not intelligent) automation-based (e.g., technology-enhanced) learning or AI-guided learning and development but did not differentiate between the distinct characteristics of these technologies. Even though a few studies have tried to outline the development from traditional technology-enhanced learning towards using AI in learning and development (Chen, 2022), the difference between these two technologies is not clearly stated with regards to employees' learning and development as well as their motivation to learn within an organization. However, the difference between simple automation and AI-based systems is not negligible. While simple automation, follows automated rules, thus does not adjust itself and has a specific focus on replacing human resources in repetitive workflows (Vagia et al., 2016), AI enables a computer system to learn from its experiences and errors and adjust to new inputs (Bhatt & Shah, 2023). As such it is of relevance to explore whether this difference may impact motivation to learn. Furthermore, the focus of prior studies has potentially been on simple automation reflecting reality so far, but as nowadays' reality is being disrupted by AI at an incredible pace (Agrawal et al., 2022), AI-guided L&D will become the new reality and thus it is vital for researchers and practitioners alike to investigate whether these new systems lead to differences in employees' motivational needs satisfaction and technology acceptance.

It therefore becomes apparent, that further research using the SDT to examine employees' motivation to use technological applications is needed. Therefore, this study employs three components of the SDT (i.e., autonomy, competence, and relatedness) as well as three UTAUT constructs (i.e., performance expectancy, effort expectancy, and social influence) to understand employees' motivation to learn with AI-guided vs. simple automation-based learning and development systems as well as their behavioural intention to actually engage with it. In my dissertation I will address the identified research gap by conducting an experimental study with employees and workers that provides answers to the following research question and consequent sub research questions.

RQ: Does the use of AI in employee L&D drive autonomous motivation to learn through self-determination more than simple automation-based L&D?

SRQ 1: What is the impact of AI on perceived autonomy, perceived competence, and perceived relatedness in regards to motivation to learn compared to simple automation-based L&D?
SRQ 2: What is the impact of AI on performance expectancy, effort expectancy, and social influence in regards to learners' willingness to engage with AI-guided vs. simple automation-based L&D systems?
SRQ 3: What is the relationship between employees' motivation to learn and their intention to use a L&D-system? Does AI impact this relationship?

1.3 Academic & Managerial Relevance

The variety of research papers dealing with different types of motivation (Gagné & Deci, 2005) and the high presence of this topic in management and business articles (Chung, 2021; Chung et al., 2022; Hagel, 2021; McSilver, 2022), serve as an indicator of the growing interest in this topic among researchers and its significance for practice (Van den Broeck et al., 2021).

This research contributes to the existing literature on AI-guided and automation-based learning and development as well as employee motivation and technology acceptance. Unlike previous studies, which have investigated the effects of simple automation-based (technology-enhanced) L&D on motivation to learn and technology adoption (Hsu, 2021; Roca & Gagné, 2008), this study compares both, simple automation-based and AI-guided L&D, within an experimental setting.

Furthermore, prior studies highlighted that further research concerning the societal and personal effects of recent AI developments is needed to better comprehend their impacts on individuals in their daily lives and at the workplace (Collins et al., 2021). Thus, this study provides insights into how employees perceive L&D systems operated by AI and thus enriches prior studies of AI-enabled systems in the workplace. As such, in contrast to previous studies which primarily focused on applying the SDT and UTAUT within a classroom setting and with predominantly student participants, this study extends the application of these theories to a more representative sample of individuals: workers and employees.

Finally, this study also follows prior researchers' call for investigating employees' adoption and use of AI tools based on the UTAUT model (Venkatesh, 2022).

In addition to its academic relevance, practitioners can also derive valuable benefits from this research. In fact, as can be seen from prior research on technology acceptance, and as outlined by Venkatesh et al. (2003), the UTAUT is an effective tool for managers to evaluate the probability of successful technology implementation and supports their comprehension of factors that drive users' acceptance. By knowing the drivers behind individuals' actions, managers can proactively intervene in the design phase of for example training initiatives targeted at users who may be reluctant to adopt and use state-of-the-art systems (Venkatesh et al., 2003). Thus, by analysing the relationships between the different UTAUT constructs and employees' willingness (e.g. intention) to actually engage with AI-guided or simple automation-based learning and development within an experimental setting, valuable insights for practitioners in terms of successful technology implementation are provided, as depending on the results of this study, practitioners will know, whether AI-guided or simple automation-based L&D is better suitable for employees' learning and development needs.

However, practitioners do not only develop a profound understanding concerning the determinants of technology adoption, but also receive insights from a Self-determination Theory perspective concerning the driving factors of people's motivation to learn and how these are impacted by the learning means. Thus, management can benefit from the knowledge of what motivational aspects employees are looking for in L&D initiatives. As having the right L&D program in place is crucial for organizational success (Naim, 2023) and motivating top talents (Chen, 2014), it is of particular relevance for companies and managers alike, to provide effective training and development opportunities targeted to the right employees with the appropriate content and thus increase not only employees' skills and capabilities, but also foster their motivation and usage.

Overall, AI technology in training and development brings benefits for both the individual and the organization and given its immense potential to push human resource management to the next level HR practitioners ought to prioritize investment in AI technology (Chen, 2022).

1.4 Structure

After this first introductory chapter, which highlights the relevance of studying the impacts of AI-guided and simple automation-based L&D on motivation to learn and behavioural intention to use, the next chapter will provide a structured review of relevant literature and theories. Thus, the main empirical findings and prior research on general workplace L&D, simple automation-based (technology-enhanced) L&D and AI-guided L&D are summarized and connected to relevant research findings on the Self-determination Theory (SDT) and the Unified Theory of Acceptance and Use of Technology (UTAUT) model. While in the third chapter, the methodology and the research design of the underlying experimental study are explained in detail, an overview of the study's main analyses and results is provided in Chapter 4. In the following Chapter 5 these results are further discussed and theoretical and practical implications as well as limitations of this study and recommendations for future research are outlined. Ultimately, in the final chapter the main conclusions of this study are presented.

2 Literature Review

The following chapter provides an overview of the status-quo of automation and AI-applications in the domain of workplace learning and development and deals with the theoretical foundations of employees' motivation to learn and technology acceptance.

2.1 Employee L&D

2.1.1 Workplace L&D

Employee training and development is one of the most essential functions in human resource management (HRM) (Vardarlier, 2020). Blanchard & Thacker (2013) describe training as an open system, highlighting that employee L&D is embedded as a subsystem in HRM, which itself represents a subunit of the overall firm. Thus, organizational and employee needs, as well as budgets for training, staff, and equipment represent inputs from the organization into the learning and development subsystem, which are transformed through training processes (e.g., learning and development) into relevant outputs such as broadened knowledge, skills, and enhanced job performance. This showcases the interdependency and dynamic relationships between L&D activities and other organizational processes (Blanchard & Thacker, 2013).

These relationships between inputs, processes and outputs are also present in the conventional training process model, widely known as the ADDIE model, which presents the major processes of training and employee L&D within organizations, including **A**nalysis, **D**esign, **D**evelopment, **I**mplementation, and **E**valuation. First, in the needs analysis phase, often referred to as the training needs analysis (TNA), the organizational performance gap (= gap between actual organizational performance and expected organizational performance) is identified and training needs are prioritised. Next, in the design phase, decisions are made regarding the training objectives and guidelines, which are then further shaped in the development phase into an instructional strategy, including the order, timing and combination of methods, materials to be used, and elements to be implemented in training initiatives to meet the outlined objectives. All the before mentioned steps are then combined in the implementation phase, in which the previously created training plan is implemented. Lastly, in the evaluation phase, processes in terms of scope achievement (e.g., outputs) and outcomes, concerning the effects of the initiative on trainee, the job, and the organization, are assessed (Blanchard & Thacker, 2013).

According to Blanchard & Thacker (2013), employee development should aim at being beneficial for both the employee and the company. Thus, without taking into consideration employees' needs, reaching high performance motivation aligned with the interests of the company is unlikely. Thus, it comes without great surprise that in recent years, employees' workplace L&D needs have shifted from traditional 'mass up-skilling' in groups to customized development needs, starting with individual needs' assessment, and resulting in employee-tailored development plans (Naim, 2023).

However, as the creation of such seamless, intuitive, and personalized learning experiences requires a lot of time and effort from HR professionals, the emergence of new technologies, such as automation and AI, provides opportunities and improvement for human resource management in terms of cutting tedious and costly processes within the training process model. In particular AI, with its capability of simulating human intelligence and thus transforming the way how organizations operate, bears huge potential for individualized L&D (Naim, 2023).

2.1.2 Automation-based L&D

With the introduction of the internet and web technologies for managing employee payroll and communication in the 1990s, HRM witnessed the emergence of technology-based HRM (e-HRM) processes, which since then have been widely spread and applied in simple HR practices, such as recruiting, skill training, and performance measurement (Sharma & Ahmad, 2022). As a consequence, e-HRM transforms and digitizes the nature of HR interactions and fosters organizational efficiency in terms of cost reduction and improved strategy by using web-based systems or mobile technologies. Advancements in technological systems include for example the concepts of e-recruitment, e-rewards, and also e-learning in employee training (Sharma & Ahmad, 2022).

As far as corporate employee training initiatives are concerned, the digitalization consists of various systems that allow employees to participate in L&D activities via communication tools independent of time and place. Thus, technology is supporting and simplifying the training process in an electronic environment (Vardarlier, 2020). In the literature, various concepts and terminologies, such as computer-based/-assisted/-aided learning/training/assessment, represent technological applications and developments in information and communication technology used for learning and teaching. Chen (2022) mentions computer-based multimedia training (CBT) technology and web-based training (WBT) technology as traditional training methods. In a similar manner, Kashive et al. (2021) describe e-learning as a set of various applications and activities such as computer-assisted learning, web-based training, virtual learning environments, and digital collaboration. Overall, these concepts integrate computers, digital devices and software with supporting telecommunication technologies and online learning (Gordon, 2014), which is referred to as technology-enhanced learning (TEL) by various scholars (Chatti et al., 2012; Gordon, 2014; Gros, 2016; Kabudi et al., 2021).

Kabudi et al. (2021) described technology-enhanced learning as technology-based learning and teaching applications which enable students to broaden their knowledge and skills via input from lecturers, tutors, tools for learning support and technological resources. Similarly, Gros (2016) presented the concept of smart learning (environments) in context of TEL and how technology usage improves learning. As concrete examples for commonly used technology-enhanced systems among students, Blackboard, Moodle, Web CT and Canvas are mentioned (Ushakov, 2017).

As can be seen from prior research, the computer-based delivery of learning objects has always been linked to TEL, and many organizations have incorporated a so-called enterprise learning management system (LMS). As an example, for TEL, these technology-aided platforms serve as the base of modern e-learning (Vieyra & González, 2020) and are used by HR professionals to plan, deliver, and manage L&D initiatives within organizations (Lal, 2015). Mostly, these platforms provide learners fixed bundles of online modules, which enable a modularization of courses and the division of learning content into smaller units (Chatti et al., 2012). Additionally, LMSs enable the streamlining of administrative work, such as allocating courses, instructors, and employees to respective training initiatives. Furthermore, LMSs support HRM in tracking employee progress, analysing development gaps, and recommending appropriate courses (Lal, 2015).

However, the main focus of current TEL solutions is on automating the learning process with the aim to control, centralize, and standardize the process via technology usage (Chatti et al., 2012). Thus, as automation is defined as an approach of making an appliance, a process or a system operate automatically (Madakam et al., 2019), automation technologies comprise substituting human labour through machines. In other words, with a core goal of automation to decrease the need for direct human involvement within business processes (Chakraborti et al., 2020), employees and workers are displaced from activities now operated via automation (Acemoglu & Restrepo, 2019).

One such emerging technology in business process automation is robotic process automation (RPA). Based on the notion of software robots that fulfil tasks previously performed by humans, it has a specific focus on replacing human resources in repetitive workflows (Chakraborti et al., 2020; Madakam et al., 2019). RPA's overall goal is to offer users easy access to automation by operating on the user interface of software applications and therefore enables the automation of mouse and keyboard interactions of repeated, routine, and labour intense activities. As a result, RPA bears the opportunity for HR managers to outsource their manual and repetitive tasks to technology such as bots, or robots and provides support in various HR functions (Pillai et al., 2022). According to Papageorgiou (2018), close to 60% of a firm's process related tasks, including data capturing, learning and development administration, and onboarding among others, can be executed from RPA. However, this automation technology is not intended to replace HR, but aims at supporting driven processes and increases the efficiency and effectiveness in the HRM system (Mohamed et al., 2022). As such, RPA enables a streamlining of operations and a reduction of costs (Madakam et al., 2019).

For business processes, RPA is used in the form of configuring software which enables the transfer of data from several input sources such as email and spreadsheets to record tracking systems such as enterprise resource planning (ERP) or customer relationship management (CRM) systems. With RPA, day-to-day rules-based business operations can be automated, and thus users can dedicate more time to customer-service and other higher-value work. Given a successful implementation of such automation technology, high performing human-robot teams, in which both humans and robots complement each other, are the outcome (Madakam et al., 2019). As such, these human-robot interactions (HRI) are mutually influential, meaning that the interaction with machines goes beyond simple usage (Kim, 2022). In fact, Ramos et al. (2020) described in their paper the iterative process, in which the "human-in-the-loop" teaches machines how to perform certain tasks, as a main characteristic of interactive machine teaching and highlighted that this interaction is potentially able to facilitate the development of machine-learned models.

But despite the fact that RPA in common LMSs enables smart working among HRM professionals via the operation of rules-based, standardized tasks, current TEL applications are directed top-down from the educational institution and follow a one-size-fits-all principle. As a result, the learning process is not tailored to individual employees, and development needs are not necessarily satisfied (Chatti et al., 2012). However, as outlined by Vieyra & González (2020), machine learning algorithms can complement the instructional content of existing LMSs and transform them into artificial intelligence-based systems (Foxall, 2018).

2.1.3 Artificial intelligence and machine learning

The interdisciplinary field "artificial intelligence", also referred to as AI, emerged as a result of the discussions held in the research project on artificial intelligence by John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon in 1956 (McCarthy et al., 2006). Scholars from all over the world discussed the possibility that "every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" (McCarthy, 1955, p. 1). Starting from this debate, AI has been largely investigated by researchers and practitioners globally (Garg et al., 2022).

McCarthy (2007, p. 2) states that AI is "the science and engineering of making intelligent machines, especially intelligent computer programs", which highlights, that AI has a broader scope and is composed of various technological developments supporting a computer in simulating human intelligence. As outlined in a previous study about change readiness towards AI in HR practices, AI enables a computer system to learn from its errors, adjust to unfamiliar inputs, and carry out tasks similar to those of humans (Bhatt & Shah, 2023). Thus, contemporary AI applications, such as AI-controlled automobiles, rely on deep learning and natural language processing (NLP) techniques, as these methods allow machines to learn to perform specific tasks by analysing data from various sources and identifying patterns (Bhatt & Shah, 2023). In fact, machine learning (ML) is a way of reaching AI by developing algorithms, which are constantly self-improved based on learnings from experience (Garg et al., 2022). As such, machine learning is supporting the intelligent automation of various parts within training and HR processes (Garg et al., 2022).

According to Naim (2023), algorithms, big data, and computational technologies represent the three main subgroups of AI technologies and form the baseline for AI's potential in various business functions, including L&D. Regarding AI applications, different forms of AI are defined (Kaplan & Haenlein, 2019). The two primary forms defined as narrow AI, which resembles human intelligence, and general AI, which is able to exceed human's knowhow in certain sizes, are most commonly applied in business operations. However, the third and most advanced level, named super AI, which is better than humans in most cases and capable of engaging in instant problem-solving, is rather theoretical than realistic in practice (Kaplan & Haenlein, 2019).

Thus, deriving from traditional RPA, the vision is Intelligent Process Automation (IPA), which utilizes AI and ML in order to keep human-dependent training at a minimum. As a result, automation of more complex tasks including decision making, insights, and analysis or the coordination and collaboration of several IPA applications is enabled (Chakraborti et al., 2020). Compared to simple automation (e.g., RPA), which can only execute tasks it is told to do, without being able to exercise any alternative or modify its actions based on changing circumstances (Vagia et al., 2016), AI can recognise patterns in data from different sources and learn from it (Bhatt & Shah, 2023). Thus, while the actions of an automated system are predetermined and the system is incapable of altering them in the future (Vagia et al., 2016), AI is capable of improving and changing itself constantly (Bhatt & Shah, 2023).

As such IPA's scope includes the whole process life cycle, starting from the identification of automation opportunities to the continuous retraining of the bots based on tracked performance and thus AI-driven automation bears opportunities to transform the way humans work (Chakraborti et al., 2020).

2.1.4 AI-guided L&D

Given its broad capabilities, AI is used in several ways in today's employee learning and development. It can support existing forms of e-learning such as computer-assisted learning, web-based training, virtual classrooms, and digital collaboration (Kashive et al., 2021) and thus many scholars have already investigated the positive impact of AI on workplace L&D.

Kashive et al. (2021) highlighted that AI helps organizations in knowing more about the learner profile and consequently makes it possible to offer learners a suitable learning environment and provide them access to the right learner network. With this learner-centric approach, AI-enabled training has the potential to transform conventional training methods, which had an instructor-centric focus, to provide customized training (Chen, 2022).

In fact, AI-enabled tools can play a vital role in building a knowledge base, mining training demand, organizational training stage, and providing feedback. In particular, when it comes to organizing training initiatives, AI-enabled systems facilitate learning with customized AI trainers (e.g., AI can prescribe an AI-based trainer profile, steaming from recorded trainer characteristics, migration climate, and research findings), individualized demand satisfaction, micro-dose learning, automated tracking of individual learning progress, AI assisted Q&A, and simulations of various scenarios. In addition, by applying AI-tools in employee L&D, the workload of HR and training professionals is reduced, while at the same time the learning, as well as employees' demand satisfaction, is improved (Chen, 2022).

Furthermore, Garg et al. (2022) provided an overview of the degree, scope, and purpose of machine learning (ML) adaption in the main functions of human resource management (HRM) and found that ML is embraced by HRM in general, however it is up to date more present and more strongly applied in recruitment and performance management, as well as in the usage of decision tress and text-mining algorithms than in complex processes, where the implementation of ML is still in its early stages and necessitates the collaboration between HR professionals and ML experts. Concerning the different functions of HRM, it is outlined that for training and development the main objectives for ML applications are to determine employees' training needs, suggest suitable courses, and evaluate the effectiveness of the training initiatives. As such, HR professionals' and scholars' focus until now was on using machine learning for employee assessment, performance prediction, training need identification, and measurement of training success and effectiveness. Thus, technology and automation has been mostly viewed as a supporting tool (Garg et al., 2022).

In general, ML in employee L&D supports the automation of various steps within the training journey. For example, chatbots are used as personal career coaches, advising employees on which trainings to attend and which materials to read (Castellanos, 2019). Furthermore, ML algorithms are used for predicting occupational levels of employees in different stages of their career, allowing HR managers to offer employees career advice and suitable training initiatives during their employment within the company (Garg et al., 2022). Thus, chatbot-based learning and virtual mentoring are part of AI-enabled workplace L&D (Naim, 2023).

On that matter, Maity (2019) has identified significant opportunities of AI in L&D based on qualitative interviews with HR professionals. In fact, it is highlighted that AI can be used for assessing employee performance through the utilization of predetermined performance measures. In addition, AI allows for a definition of training demands by linking performance ratings and employee characteristics to knowledge, skills, and abilities (KSAs) and thus enables professionals to identify gaps. Moreover, through AI-enabled L&D, learners' preferred training method, and trainer characteristics can be identified. Thus, an optimal fit between trainers and trainees can be fostered. Regarding the training initiative itself, AI makes it possible to suggest an adequate duration, frequency, pace, and delivery mode for the training initiative. In addition, AI can improve knowledge creation and documentation within organizations and thus steer knowledge management processes. In terms of decision making, AI enables organizations to prevent human biases when nominating and selecting employees for certain training initiatives. For example, by training AI to disregard individual's physical appearance or other personal attributes, the focus can be shifted particularly towards assessing specific skills and behaviours (Hunkenschroer & Luetge, 2022). Moreover, training transfer and individual development of the employee can be measured via relevant parameters, and based on the results, appropriate training programs tailored to employees can be scheduled throughout the year to increase engagement levels (Maity, 2019). Overall, AI enables the creation of end-to-end learning modules, covering the mode of L&D delivery and scheduling of L&D initiatives (Naim, 2023).

2.1.5 AI-guided learning systems in practice

In light of AI's potential, numerous AI-powered learning systems have emerged. Kabudi et al. (2021) mentioned in their paper, intelligent tutoring systems, adaptive learning systems and recommender systems as appropriate examples of AI-enabled learning environments. While intelligent tutoring systems use AI to imitate a human tutor and aim at improving learning by granting enhanced learner support (Hasanov et al., 2019), recommender systems, which are software tools operating on the basis of ML and information retrieval techniques, recommend possible helpful items to individual interests (Syed et al., 2017). Adaptive learning systems are defined as personalized learning platforms, that readjust the L&D offer based on learners' learning strategies, order, and complexity of the task fulfillment, as well as time of feedback and learners' desires. As a result, learners can track their learning progress via automated feedback mechanisms within the learning system and are thus able to continue their learning journey without a course instructor (Pliakos et al., 2019).

There are several other examples of AI-enabled learning environments, which support learners in teaching courses, such as for example, AutoTutor, OPERA or Squirrel AI (Kabudi et al., 2021). Further platforms for teaching and learning languages are QuizBot, E-Tutor, Sparrow or QuestionIT, and students' performance through personalized learning can be improved with systems such as Adaptive Mobile Learning System (AMLS) or INSPIRE (Kabudi et al., 2021).

Replacing the HR manager through an AI instructor and thus offering employees an intelligent training system, is another example of AI-enabled learning systems (Jia et al., 2018). In such systems, AI technologies can support organizations in developing a learning culture without the common teaching design model, where HR managers themselves need to identify gaps of learners via various methods (Jia et al., 2018). The instructor within the training process is artificially intelligent and thus capable of visually scanning and monitoring the learning status of students and additionally can compute average values of learners' attention. As a result, teaching events of varying stimulation levels can be retrieved via data analysis and AI instructors can modify the level of relaxation and teaching pace based on the feedback of students. In addition, by using big data analysis, corporate L&D can identify individual employees who require training from an expansive repository of knowledge and intelligently recommend and create need-tailored programs (Jia et al., 2018). Throughout the training, AI technology can then further assist learners in automatically capturing training data, which is then analysed and thus presents training managers the degree and effectiveness of employee training, which saves them time and allows for a quick comprehension of the training outcomes. Thus, AI instructors cannot only enhance the quality of learning, but also improve learning efficiency and significantly cut operation and management effort for both online and offline training. In other words, AI instructors can serve as all-round assistants, from analysing statistical learning data and generating high-quality learning reports to supervising learners and automatically ranking their performance (Jia et al., 2018).

Overall, AI-guided L&D can redefine the fundamental logic of instructional design, as employees can simply input their learning objectives, their learning records and key learning points and the AI instructor will then automatically generate the course (Jia et al., 2018). Thus, within the training and development function of HR departments, AI technology such as knowledge discovery, big data analytics, optical character recognition (OCR), intelligent robots, natural language processing and voice interaction contribute to an intelligent training system (Jia et al., 2018).

2.1.6 Benefits of AI-guided vs. automation-based L&D

Given the various AI applications, AI-guided L&D brings several benefits for employees compared to simple automation-based L&D. For example, AI-enabled learning and development can help to better understand a learner's profile and thus divide and target users accordingly. This is of particular relevance, as learners differ in their age, gender, qualification, professional and cultural experience, and background, and thus need to be targeted with unique learning and development solutions based on their individual needs (Kashive et al., 2021). Furthermore, enhanced learning experience, flexible time management, immediate feedback, flexible learning experience management, and a speedier learning progress are highlighted as benefits of AI-enabled learning systems (Kabudi et al., 2021).

Further potential benefits of AI-guided learning as outlined by Bhatt & Muduli (2022) include a reduction of complexity and improvement of completion time (Pandey, 2017), automated pre- and post-learning processes (Pappas, 2017), as well as analytics and data monitoring (Frasson & Aımeur, 1998). Furthermore, human emotions can be recognised by an AI-guided learning system through empathetic technology, which allows AI to tailor its behaviour specifically to employees' needs (Bankins & Formosa, 2020), and a larger size of learners can be targeted at once (Savino, 2014). AI-guided learning thus results in more flexible, efficient, and convenient learning initiatives for learners (Stone et al., 2015).

In addition to being beneficial for learners themselves, potential AI applications in L&D also help the overall organization by reducing the effort concerning survey-analysis in order to determine L&D needs and learners' characteristics, as well as by fostering fairness in employee selection for training initiatives (Maity, 2019). By applying AI in L&D, learning in general and required training transfer is increased due to the right match between training/trainer and learner preferences, and due to a learner-centric and personalized design. In addition, knowledge resource management within organizations is enhanced and L&D professionals are able to invest more time in the development of training strategies, the promotion and monitoring of training transfer and the innovation of training methods. Furthermore, AI enhances the interactivity and inherent engagement of L&D, thereby promoting employees' motivation to participate in L&D initiatives (Maity, 2019).

Similarly, Chen (2022) highlighted improved employee motivation and productivity in the workplace as a result of HR practices' dependence on AI tools. However, the study also found that even though AI tools radically transform organizational training, they also bring about new challenges which have to be dealt with as they might outweigh the benefits, such as rising technology costs, issues with data privacy, job substitutability of HR personnel, fairness in training, evaluation issues of training results, and negative attitudes (Chen, 2022).

So, the question is, how do people react to AI-guided L&D and what are their expectations to work with it? Are they willing to accept it? And if so, what is the impact on employees' motivation to learn?

2.1.7 Employees' expectations to work with AI

Previous scholars have outlined that individuals' perception of robots is essential for human-robot interaction, as negative feelings about robots could lead to employees' avoidance of these technologies (Nomura et al., 2006). Regarding that issue, Chen (2022) has outlined several negative attitudes of employees towards AI technology. The author refered to the so called no-human-interaction (NHI) attitude, which is defined by Lichtenthaler (2020) as a pessimistic attitude towards engaging with artificial intelligence. As such, the reluctance of some employees to embrace AI in the workplace can, for example, steam from their fear of job displacement, as a result of the technology's capability of substituting human labour (Winick, 2018). Similarly to these doubts about future employment, stiffness to change when faced with technology failure has negative impacts on AI acceptance (Bhatt & Shah, 2023). In fact, employees, who have a low technology readiness (e.g., preparedness and willingness towards new technology acceptance and usage for work related goals), might experience feelings of insecurity and discomfort, when interacting with new technologies, which in turn could lower their motivation and productivity (Parasuraman, 2000). In addition, the absence of organizational regulations concerning integrity and safety affects employees' trust in interacting with intelligent machines (Sanders et al., 2019).

Indeed, trust plays an important role when determining employees' expectation to work with AI. And transparency in particular is crucial for successful collaboration, in which employees willingly acknowledge facts provided by robots, accept their advice and anticipate interactions (Hancock et al., 2011). On that matter, it was found that introducing algorithms in formal decision-making processes inevitably affects the behaviour and experiences of employees (Tambe et al., 2019). In particular, the relationship between supervisor and subordinates, which is important for employees' performance, is affected. As this relationship is strengthened through social interactions, algorithmic decision-making could harm it and could then lead to employees not accepting decisions, as no goodwill with the machine can be established and thus no empathizing is possible (Tambe et al., 2019). In fact, it was found that human-related factors, such as personal experiences and know-how, are important determinants of employees' trust in intelligent machines (Sanders et al., 2019).

However, while missing "human touch" and preferring human over machine interaction are crucial factors for employees being unsure or hesitant to accepting AI technology, it was also found that an artificially intelligent machine can show a human-like mindset, in terms of solving problems and learning by its own (Bhatt & Shah, 2023). Furthermore, employees' perceptions about their robot peers vary depending on their individual background, experiences, and capabilities. For example, people who are knowledgeable with technological solutions and possess a general understanding of robots tend to be more receptive to interacting with them (Bartneck et al., 2007; Soh et al., 2020). In fact, Bhatt & Shah (2023) highlighted that previous researchers have found five factors which positively impact employees' acceptance of AI in HR practices. First, people's positive attitude towards change, in terms of expecting AI to be advantageous, due to convenient, employee-tailored measures as well as representing a more efficient and rewarding learning technology is mentioned. Furthermore, creativity is seen as crucial for AI acceptance as it leads to employees' openness in accepting AI technology. Lastly, self-efficacy, in terms of employees' belief of their own capabilities in adopting AI solutions is considered as a factor influencing AI acceptance (Bhatt & Shah, 2023).

In regard to employee learning, prior research highlighted that artificial intelligence can enhance learners' personal learning environment and thus can positively impact learners' overall attitude and satisfaction of e-learning initiatives. In particular, learners' perceived ease of use and usefulness is increased when AI applications in traditional e-learning are used (Kashive et al., 2021). Moreover, users' satisfaction and perceived ease of use then impact the intention to engage with an e-learning system.

In general, it seems that a supportive climate can influence employees' positive feelings towards training initiatives and can positively shape how they perceive possible benefits of taking part in a training program which then can lead to an increased understanding of their strengths and weaknesses and as a result increases their motivation to learn (Chung et al., 2022). Thus, supporting managers, supervisors, and peers, as well as organizational help, in combination with a steady learning culture, positively influence employees' motivation to learn (Chung et al., 2022).

Given people's diverse expectations and attitudes towards working with AI-guided systems, it is therefore essential to understand learners' needs and motivations (Kashive et al., 2021) to improve their satisfaction and intention to use the provided system in the long-run.

2.2 Motivation to learn

As outlined by various scholars, motivation (to learn) plays a major role not only in face-to-face training and development, but also in (online) learning environments (Chiu et al., 2023; Kashive et al., 2021; Pedrotti & Nistor, 2016; Wang et al., 2019). Chen et al. (2022) highlighted that particularly creators and professionals of technology-enhanced language learning environments should emphasize with learners' motivation to design compelling programs.

Following Colquitt et al. (2000) and Kanfer (1990), "training motivation" is defined as the direction, intensity, and endurance of learning-focused attitude during training situations (Chung et al., 2022). Based on this definition, Colquitt et al. (2000) developed a first theory concerning training motivation, with "motivation to learn", which is explained by Hicks (1983) in terms of a learner's eagerness to study training materials and to implement newly acquired abilities within the workplace, as main focus. Chung et al. (2022) built a new and thorough theory of training motivation based on Colquitt et al. (2000), taking into consideration the technology-based training methods, which have evolved since the study of Colquitt et al.

(2000). They found that the initial relationships between some of the ancestors and motivation to learn potentially are influenced by the training delivery method (Chung et al., 2022). It therefore becomes important to evaluate whether AI-guided L&D can increase employees' motivation to learn compared to simple automation-based L&D.

2.2.1 Self-determination Theory

Motivation was already studied by many scholars and various motivational theories have been developed (Van den Broeck et al., 2021). The Self-determination Theory (SDT), which originated from Deci (1971) is to date still one of the most thorough views on people's motivation (Van den Broeck et al., 2021) and has been successfully used in various fields, including education, work motivation and management (Deci et al., 2017). According to the SDT, the nature of employees' motivation for their job activities has an impact on both their job performance and well-being. Thus, the SDT distinguishes between various types of motivation and asserts that these different types are linked to different triggers, accompanying factors, and outcomes. According to the SDT, people, who pursue an activity with a complete sense of willingness, volition, and choice exhibit autonomous motivation. Generally, autonomously regulated activities are based on intrinsic motivation, which "refers to activities for which the motivation lies in the behaviour itself" (Deci et al., 2017: p. 21).

However, according to Deci et al. (2017), for employees' work setting more significant is extrinsic motivation (e.g., performing an activity with the intention of achieving a tangible or intangible consequence). Under certain conditions (e.g., performing an activity with authenticity and vitality), this extrinsically motivated behaviour can be autonomously driven or internalized (Deci et al., 2017; Roca & Gagné, 2008). Thus, employees who have a clear understanding of the value and purpose of their job and thus experience feelings of ownership and autonomy in their work, and obtain precise feedback and help, are more likely to be autonomously motivated. As a result, their performance, learning, and adjustment is improved. This is opposed to controlled motivation, which regulated through satisfying rewards or power dynamics, may limit the scope of employees' efforts. Consequently, the focus shifts to short-term gains on specific outcomes, resulting in negative spillover effects on consecutive performance and work engagement (Deci et al., 2017).

According to the SDT, people have numerous individual extrinsic motivations of why they engage in a certain activity (Deci et al., 2017; Deci & Ryan, 2000). However, depending on the degree of internalization, extrinsic motivation can be more or less autonomous (Deci et al., 2017; Roca & Gagné, 2008; Ryan & Connell, 1989). Thus, external, introjected, identified, integrated and intrinsic motivation can be presented on an autonomy scale, where external is the least autonomous and intrinsic the most autonomous form of motivation (Deci et al., 2017). For example, introjection or introjected behaviour regulation is driven by the involvement of the ego, the perception of internal pressure and guilt or feelings of self-worth. Even though this regulation is internal to the individual, it is still considered to be a controlled form, similar to external regulation. However, it is different to identification, which represents an autonomous form of motivation, where certain values or regulations are considered as meaningful and important to oneself and helpful to pursue personal values and goals. Even though identified regulation is similar to intrinsic motivation, the reasons of why people engage in a certain behaviour is different. Whereas for the first one, instrumental reasons, such as achieving a personal goal are the driving factors, the latter one refers to people's engagement given its playfulness (e.g., behaviour out of enjoyment) (Roca & Gagné, 2008).

On that matter, Lim & Kim (2002) highlighted that personal willingness drives intrinsic motivation. They investigated the impacts of learner characteristics and motivation types on online learners' learning and learning applications in language learning and found that learners experience feelings of enjoyment and show willingness to learn for their own purposes. Opposed to intrinsic motivation, external motivation stems from the anticipation of accomplishing specific educational objectives, such as obtaining a diploma or certification, or fostering professional skills (Lim & Kim, 2002).

In summary, the SDT can be seen as a macro theory of human motivation based on intrinsic and extrinsic motivation (Deci et al., 2017) and states that extrinsic motivation can be internalized, which allows for an autonomous regulation (Roca & Gagné, 2008). This means that one has the perception of being in full control of ones' values, goals and structures and is therefore capable of internally regulating one's behaviour, opposed to behaviour regulated by external factors such as rewards or punishments (Roca & Gagné, 2008). Thus, individuals who are intrinsically motivated strive for perceived competency and self-determination (Deci & Ryan, 2000).

In fact, the theory further states that humans have three basic psychological needs for autonomy, competence, and relatedness. And prior research has outlined that people are more likely to perform better in an activity and are thus more motivated and energetic to engage in further need fulfilling activities when these needs are satisfied. The level of satisfaction, however, depends greatly on the context surrounding an activity (Deci & Ryan, 2000; Roca & Gagné, 2008).

2.2.1.1 Perceived Autonomy

In the SDT, the need for autonomy refers to humans' desire for self-organizing their actions and thus being able to voluntarily engage in any activity they perceive as freely chosen. For example, people with a strong autonomy orientation choose jobs that are aligned with personal goals and interests, rather than restricted by control and coercion (Deci & Ryan, 1985, 1987). Thus, when employees are highly autonomy oriented, their intrinsic motivation is increased and as a result they are potentially more self-determined in their behaviour when it comes to extrinsic rewards (Deci & Ryan, 1985). In an educational context this means that learning environments, which are personalized and thus supportive of learners' choices and interests, can lead to an increase in a learner's perceived autonomy and competence (Garn & Jolly, 2014). Furthermore, the connection between learning goals and learners' educational and professional development, should be meaningful (Lee et al., 2015). Therefore, according to Alamri et al. (2020), the personalization of online learning initiatives, which contain relevant curriculums tailored to learners' needs and interests, can lead to more autonomously motivated learners. This becomes particularly relevant in self-regulated online learning settings, where autonomy is considered as an essential component of motivation (Chen & Jang, 2010). On that matter, Lee et al. (2015) named various strategies on how student engagement and thus autonomy within online courses can be increased, such as offering students choices, clearly explaining the purpose and logic behind course assignments and giving students the opportunity to engage in personalized and meaningful learning activities. In fact, personalized learning principles consisting of personalized instructional goals, personalized instruction focused on learners' interests, personal learning choices, learner control and personalized assessment and evaluation, which can be implemented in an online course, offer learners customized learning schedules that target personal learning needs and interests (Alamri et al., 2020). Moreover, Kashive et al. (2021) found that the personal learning profile and the personal learning network are positively impacted by AI, considering the technology acceptance of e-learning. It is shown that personal learning profile has a direct impact on a learner's satisfaction, for example when the learner's correct profile is matched with the course contents. Based on these above-mentioned findings, concerning perceived autonomy, I hypothesise that:

- ***H1:*** *AI-guided L&D leads to a higher perception of autonomy, which in turn leads to higher motivation to learn compared to simple automation-based L&D.*

2.2.1.2 Perceived Competence

According to the SDT, the need for competence is satisfied when individuals receive positive feedback and thus believe that they are effective regarding task performance and their interaction within their surroundings (Deci & Ryan, 1985). Cognitive Evaluation Theory (CET) further posits that intrinsic motivation increased when people received positive feedback compared to no feedback and that feelings of competence will only enhance intrinsic motivation if people's perception of competence is linked to people's autonomy (Deci & Ryan, 2000; Vallerand & Reid, 1984). In a learning context, the SDT highlights that instructors should provide learners with tasks and challenges suitable to their level and give feedback on their performance (Alamri et al., 2020). Thus, by providing learners with learning options that are meaningful, feelings of competence among learners can be fostered (Garn & Jolly, 2014). Pertaining to that, AI can facilitate L&D by providing an accurate pace of learning and personal assistance. Thus, depending on the specific individual learning style of each employee, AI can suggest an appropriate effective methodology and provide personalized feedback and self-evaluation (Kashive et al., 2021). As a result, AI-enabled learning and assessment allows for a more customized learning experience in which progress can be tracked incrementally through log files and click-stream analysis (Crossley et al., 2016). Given these characteristics of AI-guided L&D systems I argue that:

- ***H2:*** *AI-guided L&D leads to a higher perception of competence, which in turn leads to higher motivation to learn compared to simple automation-based L&D.*

2.2.1.3 Perceived Relatedness

Although the SDT states that autonomy and competence are the main drivers for motivation, the chance of individuals to contribute to community goals is increased, when they feel connected and supported by others. As such, perceived relatedness pertains to an individual's feeling of establishing satisfying social bonds (Deci et al., 1991). Thus, when individuals develop feelings of relatedness within autonomy-supportive systems, their motivation is increased (Deci & Ryan, 2000). With regard to learning, learners' sense of relatedness to their environment can be increased through an effective interaction and communication between instructors and other students. Furthermore, when learners have purposeful relationships within their learning community, their relatedness can be fostered and they feel at ease when interacting and communicating with other learners (Nukta et al., 2011). Thus, the SDT stresses that when learning environments are aligned with personal learning interests, feelings of learners' relatedness and competence will be increased (Garn & Jolly, 2014). Wang et al. (2019) identified relatedness as a main driver for students being autonomously motivated, when testing the relationship between learners' need satisfaction, motivation, and the various impacts of the three psychological needs in a classroom setting. According to their study, autonomy, competence and relatedness positively impact autonomous motivation, which leads to higher enjoyment, value and lower pressure. However, controlled motivation was found to be negatively related to the three psychological needs. Moreover, Kashive et al. (2021) mentioned the absence of motivation and interest among learners as main challenges of e-learning initiatives opposed to instructor-led learning, given the lack of human contact. Similarly, Alamri et al. (2020) found that even though learners' feelings of autonomy and competence could be increased by incorporating personalized learning principles in online courses compared to one-size-fits-all courses, learners still lacked a feeling of relatedness. Even though they felt related to their instructors in both courses, they lacked relatedness with their peers and fellow students. In particular, the lack of assistance through advanced technology platforms, including adaptive learning technology which supports personalized instructions, was mentioned as a main limitation of their study (Alamri et al., 2020). However, other scholars found all three psychological needs (autonomy, competence, and relatedness) to be powerful indicators for learners' motivation to use LMOOCs (Language Massive Open Online Courses), a new platform of computer assisted language learning (CALL) (Hsu, 2021). In similar manner, Maity (2019) highlighted that AI makes L&D interactive and naturally engaging and thus improves employees' motivation to engage with L&D programs. As AI in employee L&D can aid learners in interacting with peers and instructors (Hsu, 2021), but also with employers, such as for example with AI-based chatbots (Guenole & Feinzig, 2018; Lee et al., 2022) and additionally enhances learners' engagement and community formation (Ferguson, 2012), I hypothesise the following:

- ***H3:*** *AI-guided L&D leads to a higher perception of relatedness, which in turn leads to higher motivation to learn compared to simple automation-based L&D.*

In summary, online educationists can draw on SDT strategies for creating learning initiatives that foster learners' autonomy, competence, and relatedness and thus promote learners' self-determined motivation (Alamri et al., 2020). Based on the relevant findings from prior studies above revised, I therefore hypothesise that:

- ***H4:*** *The mode of L&D delivery impacts motivation to learn, such that AI-guided L&D leads to higher motivation to learn than simple automation-based L&D.*

While, according to prior research it seems that AI in L&D can enhance employees' motivation to learn, it also becomes relevant, to investigate employees' willingness (e.g., intention) to actually engage with these new modes of L&D delivery. Particularly for systems including AI, which can be viewed as an actor within a system, and thus requires that employees accept the new technology and learn how to work with it (Anthony et al., 2023), investigating employees' intention to use new technological solutions is important. In fact, previous studies have outlined that it is not self-evident whether individuals' motivation (to learn) automatically results in their intention to use and adopt a new technology (Hsu, 2021; Melenhorst et al., 2006). However, motivation and students' learning in technology-enhanced contexts was found to be positively correlated (Sun & Gao, 2020). Thus, knowing the drivers behind individuals' actions, allows managers to proactively intervene in the design phase of for example training initiatives targeted at users who may be reluctant to adopt and use state-of-the-art systems (Venkatesh et al., 2003). Therefore, it becomes relevant to evaluate whether AI-guidance in L&D can also increase employees' behavioural intention to use a L&D system compared to simple automation. Based on the above revised, I hypothesise that:

- ***H5:*** *The mode of L&D delivery impacts the behavioural intention to use the L&D program such that AI-guided L&D leads to a higher behavioural intention to use compared to simple automation-based L&D.*

2.3 The Unified Theory of Acceptance and Use of Technology

A first model to conceptualize users' acceptance and use intention of information systems (IS) was introduced by Davis (1985). Since then, his initial Technology Acceptance Model (TAM) has been applied by various scholars and over time, new hypotheses in regard to this initial model have been tested in various contexts and with different variables. As a result, researchers have further adapted the model and created updated versions of it (Lai, 2017).

One of the recent models that concentrates on the intention to use is the UTAUT (The Unified Theory of Acceptance and Use of Technology) model, which was first proposed by Venkatesh et al. (2003). It provides a holistic view on usage intention by combining eight widely recognized technology acceptance models, namely the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), the Technology Acceptance Model (TAM) (Davis, 1985), the Motivational Model (MM), the Theory of Planned Behaviour (TPB) (Ajzen, 1991), the combined TAM and TPB (Taylor & Todd, 1995), the Model of PC Utilization (MPTU) (Thompson et al., 1994), the Innovation Diffusion Theory (IDT) (Rogers, 1995), and the Social Cognitive Theory (SCT) (Bandura, 1999) (Bakar et al., 2013; Lai, 2017; Venkatesh et al., 2003).

The original UTAUT model consists of four major UTAUT variables: performance expectancy, effort expectancy, social influence and facilitating condition. However, only the first three variables directly impact the behavioural intention to use. Facilitating condition, as a fourth major construct, does not directly impact the behavioural intention to use, but directly impacts use behaviour. The variables gender, age, experience, and voluntariness of use serve as moderators in the original model (Venkatesh et al., 2003).

Performance expectancy in the initial UTAUT model developed by Venkatesh et al. (2003, p. 447) is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance", while *effort expectancy* indicates "the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450) and *social influence* is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003, p. 451). As the underlying study focuses on employees' willingness (e.g., behavioural intention) to use simple automation-based or AI-guided learning and development systems, and the actual *use behaviour* of employees is not investigated within the scope of this study, only the variables, which directly impact individuals' intentions to use the technology were included in the subsequent analysis. Thus, the variables *use behaviour* (e.g., the actual use of information technology) (Venkatesh et al., 2003) and *facilitating condition*, defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al., 2003 p. 453) were not included in my conceptual model. This decision goes in line with Wan et al. (2020) who found that while performance expectancy, effort expectancy and social influence had a statistically significant impact on continued intention to use MOOCs for learning, facilitating condition did not directly impact learners' use intention. In similar manner, Chen & Hwang (2019) did not include facilitating conditions as well as use behaviour in their study, as they also only aimed at investigating the behavioural intention of using an online learning system.

Initially constructed to generate a unified view of user acceptance of new information technology (IT) in the work environment, the UTAUT has been used in recent years to investigate acceptance and use behaviour for e-learning (Yoo et al., 2012), web-based learning (Chiu & Wang, 2008), online learning (Batucan et al., 2022), tablet personal computer (Scholar et al., 2006), email (Yamin & Lee, 2010), student portal (Bakar et al., 2013) and sport apps (Guo, 2022) and was also lately used to investigate usage intentions for AI-related technology (Andrews et al., 2021).

For example, Lin et al. (2022) investigated the adoption of AI-enabled language e-learning systems among users of online learning products in China with an extended version of the UTAUT and found that while effort expectancy and social influence significantly impacted adoption behaviour, performance expectancy was not found to be a significant predictor. Similarly, Isaias et al. (2017) used the UTAUT as a framework to investigate the acceptance among students of an educational forum, used in mobile and distance learning, which incorporates empathic AI-based technologies. They found that in particular social influence had a positive influence on students' behavioural intention to use emphatic forums, while performance expectancy, effort expectancy and facilitating conditions were considered irrelevant.

In addition to these previous UTAUT applications by various scholars in the context of general learning, the UTAUT has also been successfully applied within work settings. As such, it was found that customer relationship management (CRM) quality and satisfaction along with performance expectancy, effort expectancy and facilitating condition are significant for organizational users' intention to use AI-integrated CRM systems (Chatterjee et al., 2021). Similarly, Jain et al. (2022) used an extended UTAUT model to investigate employees' use of AI-enabled tools for collaboration in social development organizations and found that performance expectancy, effort expectancy, facilitating conditions and social influence as well as algorithmic aversion significantly affect employees' usage of AI-enabled tools. They also found that social influence had the strongest impact on AI-enabled tool usage in the organization. Furthermore, the UTAUT model was also applied in a human resource management context to analyse the effectiveness of e-HRM practices. In line with the original UTAUT model, the significant positive effect of performance expectancy, effort expectancy and social influence on behavioural intention to use e-HRM was confirmed (Kwan et al., 2019).

Based on these various UTAUT applications, it becomes apparent that the variables' predictabilities are not clear-cut and vary depending on the context in which they are applied (Devolder et al., 2012). Thus, it is relevant to analyse the impacts of simple automation-based and AI-guided learning and development on employees' behavioural intention to use a L&D system in an organizational context within this study.

As outlined by prior research, AI in L&D can result in a speedier, more authentic and more inexpensive learning process, for a larger set of learners and fosters the flexibility, efficiency, and convenience for learners (Bhatt & Muduli, 2022). Furthermore, AI-guided L&D makes learning less costly for learners, while at the same time enhancing their creativity, engagement, and the development of communities within the learning environment (Bhatt & Muduli, 2022). Given these distinct characteristics of AI-guided L&D and the significant findings concerning performance expectancy, effort expectancy and social influence in an AI context of prior studies, I make the following hypotheses:

- ***H6:*** *AI-guided L&D leads to higher performance expectancy, which in turn leads to a higher behavioural intention to use compared to simple automation-based L&D.*
- ***H7:*** *AI-guided L&D leads to lower effort expectancy, which in turn leads to a higher behavioural intention to use compared to simple automation-based L&D.*
- ***H8:*** *AI-guided L&D leads to higher social influence, which in turn leads to a higher behavioural intention to use compared to simple automation-based L&D.*

Based on the research findings from the UTAUT applied to AI-guided L&D it becomes evident that employees' technology acceptance is an important factor to consider when implementing new L&D solutions. However, as outlined by Hsu (2021) the relationships between the UTAUT components are not definite and thus potential moderator variables exist. The final question in this thesis therefore is how employees' self-determined motivation to learn and their technology acceptance are related to each other.

2.3.1 Motivation to learn and Behavioural Intention to use

Researchers have already considered intrinsic motivation as an important variable when explaining learners' use of information technology (Lee et al., 2015; Roca & Gagné, 2008). Roca & Gagné (2008) investigated which role perceived autonomy, perceived competence, and perceived relatedness play, when explaining the impact of intrinsic and extrinsic motivation on the continuing use of Information Technology (IT) in the workplace and found that the SDT can be used to show how organizational factors influence users' motivation and highlighted that a feeling of autonomy and competence is decisive whether users are willing to continue using IT. This is because these basic needs impact users' intrinsic and extrinsic motivation as well as perceived usefulness and perceived playfulness, which both influence users' intentions of continuing IT usage. The study also found that when employees feel connected and supported by others (perceived relatedness), for example by colleagues, they use IT (learning) systems due to personal enjoyment (Roca & Gagné, 2008).

Similarly, Yoo et al. (2012) found that intrinsic motivators have an impact on employees' intention to use technology in an e-learning context, which is in alignment with Chiu & Wang (2008) who reported intrinsic motivation (i.e., playfulness) among others as a significant predictor of learners' intentions to continued usage of web-based learning. Also, Pedrotti & Nistor (2016) explored the connection between technology acceptance and learners' motivation and proposed to include intrinsic motivation into common technology acceptance models, in order to gain a deeper comprehension of individuals' attitudes regarding learning technology usage, as for example online learning management systems.

Prior scholars also found favourable connections between the three SDT components and learners' behavioural intention to use e-learning systems, when combining the SDT with an extended version of the UTAUT, the UTAUT 2 as proposed by Venkatesh et al. (2012), which includes next to the original constructs, also hedonic motivation, price value and habit as predictors of behavioural intention (Osei et al., 2022).

Finally, Hsu (2021) highlighted in his study, in which he investigated the relationship between learners' self-determination and their acceptance of language massive open online courses (LMOOCs) built on the UTAUT model that all three psychological needs (autonomy, competence, and relatedness) are significant to learners' motivation to use and thus learners' self-determination has a positive impact on LMOOC use behaviour.

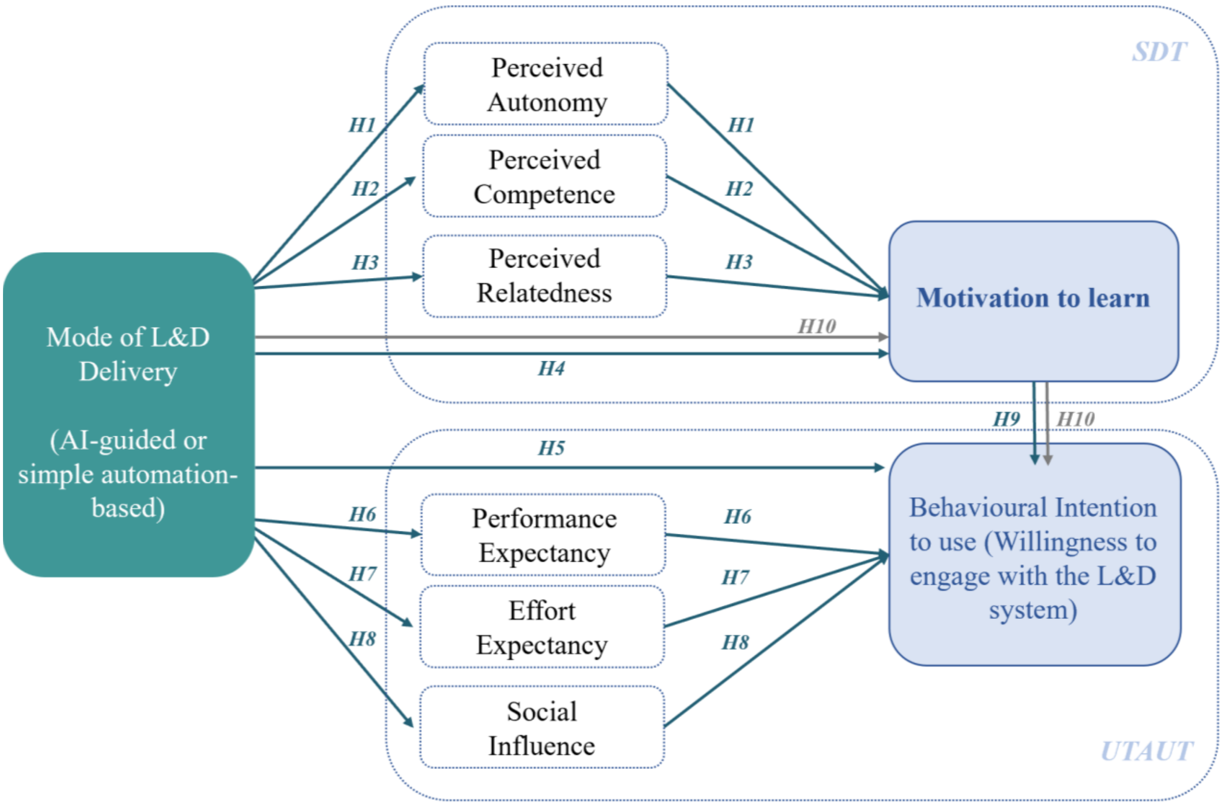
Based on these prior research findings, of how intrinsic motivation, composed of the three SDT components, impacts learners' usage intentions of new technology, my final hypotheses read as follows:

- ***H9:*** *Motivation to learn has a positive impact on the behavioural intention to use the L&D program.*
- ***H10:*** *AI-guided L&D leads to higher motivation to learn which then leads to a higher intention to use compared to simple automation-based L&D.*

2.4 Proposed conceptual model based on the SDT and the UTAUT

The following conceptual model combines all above-mentioned hypotheses and highlights the relationships between the various variables used within this thesis.

Figure 1 Proposed conceptual model based on the SDT and the UTAUT



Note: H1 = Hypothesis 1; Hypothesis 2-10 respectively

3 Methodology

The aim of the following paragraphs is to outline how the above proposed research questions were tested. Thus, an overview regarding the underlying research strategy and design, the data collection and sample, as well as the experimental procedure is provided. Furthermore, relevant details in terms of variable measurement and applied scales are presented.

3.1 Research strategy and design

The main objective of this dissertation was to assess how knowing the source of guidance within L&D programs (e.g., mode of L&D delivery) impacts employees' motivation to learn. Thus, to examine whether AI in employee learning and development drives autonomous motivation to learn through self-determination more than simple automation-guided learning and development, an experimental design was chosen. Such experimental studies allow to test for cause-effect relationships (hypotheses) in a closely controlled environment and enable a timely separation of the cause from the effect (Bhattacherjee, 2012).

Furthermore, in line with prior research, which aimed at investigating individuals' acceptance of technology in a Self-determination Theory context, I chose a quantitative methodology for data collection to gain answers about people's perceptions of AI-guided and simple automation-based L&D. Therefore, I created an online study via Qualtrics, which is a simple to use web-based survey tool and allows for a random assignment of participants to different scenarios (Weber, 2021). Such randomization played a crucial role in ensuring a true experimental design, as its absence could have led to a quasi-experimental design (Bhattacherjee, 2012). In one experimental setting participants were presented with an AI-guided L&D process, whereas in the other they had to imagine being guided by simple automation. Thus, such a between-subject design made it possible to compare responses of individuals from different treatment conditions because the cause was only assigned to one group of participants (e.g. the "treatment group") but not to the other (e.g., the "control group"). In fact, due to the implemented manipulation of the independent variable, a deduction of causal relationships and mean effects between participants in these two groups was enabled (Bhattacherjee, 2012; Charness et al., 2012). Furthermore, sensitization and carry-over effects commonly present in within-subjects experiments were decreased and threats to internal validity were reduced (Greenwald, 1976). This is in line with prior research which stated that the main strength of an experimental design is represented by its powerful internal validity given the ability of isolating, controlling, and closely investigating a small number of variables. At the same time, however, the strongest flaw of such a design is its reduced external generalizability, given the often times more complex real-life situation compared to the overly planned experimental settings (Bhattacherjee, 2012). Thus, by formulating the scenarios as realistically as possible by ensuring that the study design was not artificially constructed and controlling for external variables and their influence on the dependent variables (DV), I tried to improve the external validity of my research design (Bhattacherjee, 2012).

The internal validity, which is also referred to as causality, assesses whether an observed change in a dependent variable can be attributed solely to the corresponding change in the hypothesized independent variable (IV), rather than being affected by external factors outside the research environment. According to Bhattacherjee (2012), an experimental between-subject design controls for the conditions of (1) covariation of cause and effect, (2) temporal precedence (3) no spurious correlation. First and foremost, because it enables a manipulation of the independent variable (cause) via a treatment (in my case AI-guided vs. simple automation-based L&D) and thus allows the investigation of the effect of that treatment on the dependent variables (in my case, motivation to learn and behavioural intention to use) once a particular moment in time is reached, while controlling for effects of additional variables. In this research this was accomplished by investigating the independent variables (IV) first, by randomly assigning participants to one of the conditions - the treatment group (AI-guided) or the control group (simple automation-based), after which a set of questions was asked with regards to the hypothetical L&D scenario participants have been presented with, measuring the DVs (motivation and behavioural intention) and the mediating variables (specific components of the SDT and the UTAUT) after.

Building on previous research that studied learners' technology adoption in a SDT and UTAUT context, a multi-stage regression modelling method was chosen for data analysis. All hypotheses were thus tested using partial least square-structural equation modelling (PLS-SEM). PLS-SEM was chosen as according to prior research, it enables an assessment of the latent variables as well as the relationships between them following an iterative approach (Matthews et al., 2018). Thus, maximisation of the explained variance of constructs can be reached. In addition, in contrast to another structural equation modelling approach, the covariance-based SEM (CB-SEM), which works best for larger sample sizes and theory testing, PLS-SEM is suitable for smaller ($n \leq 100$) and larger sample sizes with reflective or formative measurement models and does not require normally distributed data. Given those reasons, and the fact, that PLS-SEM can also be used to test multiple mediation in which all relationships (e.g., direct and indirect) are evaluated simultaneously, PLS-SEM was chosen to be suitable for the underlying research (Matthews et al., 2018).

3.2 Procedure

To test the outlined hypotheses and the conceptual model, an English version of the survey was designed via Qualtrics and the link to the online survey was shared to employees and workers of my personal and professional network via Social Media (Instagram, Facebook, LinkedIn), WhatsApp and via mail. Additionally, reddit and in particular the subreddits r/SampleSize, r/SampleSize_Dach and r/Automate, were used to recruit participants for my Qualtrics survey. Participants could choose on a voluntary basis whether or not they wanted to contribute to this study. Furthermore, no extrinsic incentives or rewards were set for successful participation.

The underlying survey of this research started with a brief introduction, by informing participants about the general procedure and duration of the survey and the overall topic under consideration. After participants agreed to the informed consent, they were randomly and evenly assigned to one of the two scenarios (AI- or simple automation-guided L&D) and were advised to imagine themselves in the scenario presented, while answering the subsequent quantitative questions as realistically as possible. In the scenarios, participants of both groups, were asked to take on the role of employees within an organization, which has implemented a new technology-enhanced L&D system. Consequently, general capabilities and benefits of this system were highlighted. Thereafter, participants in the AI scenario were provided with a short explanation of what in particular AI-guided L&D means for their L&D and similarly, participants in the simple automation-based scenario were informed about simple automation in the context of L&D. The information provided was based on relevant findings from prior research analysed during the literature review phase of this research (Acemoglu & Restrepo, 2019; Kabudi et al., 2021).

In specific, in both scenarios participants were informed about the main difference between AI and automation in that sense, that while AI enables a computer system to learn from its errors and adjusts to new inputs, the simple automation-based system follows automated rules, and thus does not adjust itself and replaces humans in repetitive workflows. Consequently, specific characteristics of AI-guided L&D and simple automation-based L&D were presented to the according groups. While the control group received the information that simple automation aids their training needs, by listing existing courses based on pre-prepared educational material, shows them an overview of their learning progress, and uses automated chatbots, which use pre-programmed messages, but does not take any decisions regarding individuals' L&D journey and cannot intelligently recommend programs, the treatment group was informed that AI is able to assess training needs and can suggest suitable courses based on employee-tailored educational materials. Furthermore, participants in the AI scenario were told that the system scans and monitors employees' learning status and thus also decides upon employees' L&D journey. In the end, the main characteristic of the two different systems was highlighted. As such, the control group was presented with information stressing that simple automation stays the same forever, unless re-programmed by a programmer, while the treatment group was presented with the fact that AI has the capability to change forever and learns from its mistakes. For a full description of the scenarios and the complete Qualtrics survey, see Appendix 1.

Following the scenario briefing, participants were asked to indicate who guides them in the outlined scenario, an AI-guided automation or simple automation. By selecting the right mode of guidance, the accuracy of the participants' response was confirmed, while by selecting the wrong mode, a statement of correction was shown to the participants. After this brief manipulation-check, participants of both conditions (i.e., scenarios) were asked adapted items from the Self-determination Theory (SDT) and the Unified Theory of Acceptance and Use of Technology (UTAUT). In between the two main parts (i.e., the SDT and the UTAUT components), a question aimed at testing participants' attention was included. After the two main parts, participants' understanding of the concepts of L&D, AI, AI-guided L&D, simple automation and simple automation-based L&D as well as their experience with the different L&D system types was queried and they were asked to indicate the level of difficulty they encountered when answering my survey. Before debriefing and thanking participants for their participation in this study, they were asked general demographic questions concerning their age, their gender, their nationality, their education and employment status, and their English language skills. In addition, participants were queried how much attention they paid when answering the questions and through which channel they accessed the survey.

3.3 Pre-tests

Given the experimental design of this study, additional attention was paid to participants' understanding of the described scenarios. Thus, pre-tests before starting actual data-collection were run in order to detect potential inconsistencies or problems participants might encounter with the study. For these tests, firstly the web-based questionnaire built in Qualtrics was shown to a non-probabilistic convenience sample ($N = 5$) and unstructured interviews were conducted. In order to prevent carry-over effects, these participants were not recruited for the actual study. The pre-test participants were randomly presented with one of the two scenarios and conducted the full-length survey either via their smartphone or PC, while being monitored by myself. Notes of any comments, pain points, or questions that arose within these pre-tests were further investigated and slight modifications to the questionnaire and scenarios were undertaken. In particular, the summary of the specific AI-guided or simple automation-based L&D characteristics was introduced and an attention check was added, given the study's lengthiness. Despite these adaptations, the average completion time for this study amounts to 10.7 minutes, which is considered acceptable for web-based studies.

3.4 Sample

Between April 24th and May 1st, a total of 151 responses were collected, which represents a net response rate of 48.8%. However, after removing two responses, because participants did not consent, and five due to the failed attention-check question, a total of 144 responses were deemed valid and taken into consideration for further investigations. Given the "10-times-rules"-method commonly used by researchers to estimate the minimum sample size required for PLS-SEM analysis, this sample size is adequate, as the minimum sample size for the underlying research model is 10-times the maximum number of arrows pointing at any latent variable in the model, which would lead to a minimum sample size of 50 = 10 x 5 (Hair et al., 2014; Kock & Hadaya, 2018; Peng & Lai, 2012). However, as this rule has been criticized in the past (Kock & Hadaya, 2018; Peng & Lai, 2012), I also considered the power for my particular hypotheses. I investigated that my total responses have at least .80 power to detect hypotheses linking two variables (e.g., *H4, H5, H9*) as according to Erdfelder et al. (2009) the power estimate for a medium sized correlation ($r = .30$, $p = .05$, two-tailed) would require a minimum sample size of 82 participants. In a similar manner, .80 power is also reached, for the bootstrapped bias-corrected mediations (e.g. *H1, H2, H3, H6, H7, H8, H10*) as the minimum required sample size for these types of hypotheses amounts to 148 participants (Fritz & MacKinnon, 2007).

The total valid sample of 144 includes 76 female (53%) and 68 male (47%) participants. Half of the participants ($N = 72$) have been randomly assigned to the treatment group and half of them (N = 72) to the control group. Their age ranged from 15 to 60 years old (M = 31.9, SD = 10.86) while 38% have completed a bachelor's degree and 28% a master's degree. The study includes participants from 19 countries, in particular 87.4% of which were from the following 5 countries, Austria (62%), Germany (14%), United States of America (7.1%), Portugal (2.9%) and United Kingdom of Great Britain and Northern Ireland (1.4%). While 71% of participants had at least moderate experience with common L&D, 55.2% had the same level of experience with simple automation-based L&D and 16.6% stated that they are at least moderately experienced with AI-guided L&D. In terms of participants' preferences concerning AI-guided and simple automation-based L&D over traditional human-led L&D, no statistically significant difference was found, as 45% of the AI scenario and 41% of the simple automation scenario would prefer AI or automation over human-led L&D. For more details on the demographics descriptive statistics, see Appendix 2 (Tables A-C).

3.5 Measurement of variables

Based on prior findings regarding the SDT and the UTAUT (Chapter 2.2 and Chapter 2.3), relevant variables for testing my research question(s) were chosen. The measures and corresponding scales (e.g., question items) used in this study were mainly adapted from relevant prior research, which tested similar relationships. To tailor the items to the corresponding scenario, only minor changes in wording (e.g., changing AI-guided to automation-based) were undertaken, while everything else within the scales was held constant. For the SDT and UTAUT constructs participants indicated on 5-point Likert scales the extent of their agreement with the corresponding statements of the items (1 = Not at all true; 5 = Very true).

3.5.1 Independent variable

Mode of L&D delivery (AI-guided vs. simple automation-based): The independent variable in this experimental research model was categorical and represented by the two different modes of L&D delivery. In each of the two scenarios, participants where either presented the AI-guided L&D system (treatment group) or the simple automation-based L&D system (control group), with only minor differences in wording (e.g., specific characteristics of AI or automation) between the two presented scenarios. Thus, differences resulting from the manipulation should not be linked to the general description of technology-enhanced L&D systems, but rather to the guidance with AI or simple automation.

3.5.2 Dependent variables

Motivation to learn: As outlined in Chapter 2.2, motivation to learn as a dependent variable was measured in this study by referring to the SDT (Deci, 1971) as it is to date still one of the most thorough views on people's motivation (Van den Broeck et al., 2021). In this study, intrinsic motivation to learn was measured using three items adapted from Hsu (2021). Sample items included "I would enjoy learning with this L&D program very much."

Behavioural intention to use (Willingness to engage with the L&D system): The second dependent variable in the conceptual model was measured by adapting the behavioural intention variable from Hsu (2021), who previously adapted it from the original UTAUT model presented by Venkatesh et al. (2003). Two items (e.g., "If my workplace offers this possibility, I plan to use this L&D program for learning.") were used to assess participants' willingness or behavioural intention to use AI-guided or simple automation-based L&D. Additionally, a question item was added, whether participants would prefer AI-guided or simple automation-based L&D compared to usual human-led L&D.

3.5.3 Mediator variables

In the SDT model all three basic psychological needs (e.g., autonomy, competence, and relatedness) need to be satisfied for an individual to be motivated (Deci & Ryan, 2000; Roca & Gagné, 2008) and thus different studies used these needs to predict learners' intrinsic motivation (Hsu, 2021; Roca & Gagné, 2008). In the underlying study *perceived autonomy, perceived competence, and perceived relatedness* acted as mediators in the relationship between mode of L&D delivery and motivation to learn. Many studies investigating SDT based their research on the Work-Related Basic Need Satisfaction scale (W-BNS; (Van den Broeck et al., 2010)), previously adapted from the basic need satisfaction at work scale from Deci et al. (2001). As the items of their study refer to motivation to work, for example "I feel like I can be myself at my job" (Van den Broeck et al., 2010), I chose this scale not to be suitable for measuring motivation to learn. Therefore, 11 items consisting of three subscales from Hsu (2021), previously adapted from Wang et al. (2019) were used to assess employees' perception of autonomy (4 items), competence (4 items), and relatedness (3 items) when engaging with AI-guided or simple automation-based L&D systems respectively. Sample items included "I would be able to decide my own learning process in this L&D program." (perceived autonomy), "I feel that I would learn very effectively with this L&D program." (perceived competence) and

"I would feel extremely comfortable when being with the other participants of this L&D program." (perceived relatedness).

In the original UTAUT model, first introduced by Venkatesh et al. (2003), performance expectancy, effort expectancy, and social influence were used to predict the behavioural intention to use technology. As within their model, the scales solely measured the impact on work in particular but not learning and development, I adapted and modified 12 items consisting of four subscales from Hsu (2021), given their L&D focus. Thus, four items were chosen to measure participants' *performance expectancy* regarding AI-guided or simple automation-based L&D. Sample items included "I would find this L&D program to be useful for my professional development." *Effort expectancy* was assessed by three items which measured employees' expectations of ease of use. Sample items included "I would find this L&D program flexible and easy to use." Finally, *social influence* was measured in the underlying conceptual model with three items adapted from Hsu (2021). Sample items included "I would use this L&D program for learning if my supervisor recommended it to me."

3.5.4 Control variables

Experience with traditional human-led L&D, Simple automation-based L&D and AI-guided L&D: Following the original UTAUT model as proposed by Venkatesh et al. (2003), experience was included as control variable in the underlying research model. For consistency, participants had to indicate on 5-point Likert scales the level of experience with the different types of L&D programs (1 = No experience; 5 = Very experienced).

Demographics: In line with prior studies, participants' gender, age, nationality as well as their educational and employment status were included (Andrews et al., 2021; Vorobeva et al., 2023). Gender was collected as either female, male, or other. Age was collected in years. Nationality was measured in a single choice drop-down format and the remaining two variables were measured in a single choice format using the options provided by Qualtrics. In addition, participants' *Understanding of L&D, Simple automation, Simple automation-based L&D, AI and AI-guided L&D* was assessed by using 5-point Likert scales (1 = Extremely bad; 5 = Extremely good).

3.5.5 Manipulation-check question

In order to test whether the manipulation (i.e., participating in an AI-guided L&D vs. a simple automation-based L&D program) worked as intended, a manipulation-check question was included. Participants had to indicate the source of guidance in a single choice format (e.g., An automated system vs. An AI automated system), followed by a confirmation of their right answer or correction of their wrong answer. This allowed not only to understand whether the text was clear at communicating the intended message but also to increase the chance it did, through the added text following it.

4 Results

4.1 Data cleaning and preparation

As a first step, raw data was transferred from my Qualtrics account to Microsoft Excel, where further data cleaning was undertaken. To facilitate this, a filter within the Data & Analysis section of Qualtrics was set and allowed me to only extract recorded responses, which showed a progress level of 100% and the status for Finished was indicated as "True". Using Microsoft Excel, the data was then further prepared for import to SMART PLS 4 software, which was utilized for further analysis. Thus, the data was checked for reverse-coded items and any missing data points. In addition, latent (i.e., constructs) and observable variables (i.e., indicators) were labelled accordingly, and categorical variables were transformed into numerical ones.

4.2 Manipulation-Check

As outlined in the previous methods chapter, a manipulation-check question was included in the questionnaire, to test whether participants indicated the source of guidance (e.g., AI or simple automation) correctly, depending on the described scenario. When analysing the results, the Chi-Square test showed that the null hypothesis (i.e., There is no association between the actual scenario and the perceived scenario.) can be rejected (p < .001), meaning that the manipulation was successful, as 65 out of 72 participants correctly indicated that they were guided by AI, while 53 out of 72 correctly stated that they participated in a simple automation-based L&D system. For those participants who did not select the correct mode of guidance, feedback upon which answer would have been correct was provided. For further information on this check, see the Chi-Square Test in Appendix 3.

4.3 Data analysis

Based on Hair et al. (2019), the following different steps appropriate for Partial Least Squares Structural Equation Modelling (PLS-SEM) analysis were undertaken in order to report this thesis' results. After addressing the preliminary considerations, such as sample size and statistical power, as well as data preparation for import into SMART PLS 4 software, the measurement model was assessed. Therefore, the factor loadings, composite reliability (CR), average variance extracted (AVE), and any convergent and discriminant validity were assessed and alterations to the model were made. After an assessment of the overall model fit, an assessment of the structural model was undertaken. Thus, path coefficients, standardized path coefficients and associated statistical significance tests, as well as R^2 values for endogenous constructs (i.e., dependent variables) of the model were reported. Finally, the indirect effects (i.e., mediations) were investigated. Thus, a two-step validation of PLS-SEM was undertaken as suggested by prior research (Hair et al., 2019; Sarstedt et al., 2021). Given the appropriate but not large sample size, bootstrapping resampling was performed with 20000 subsamples, percentile bootstrap as confidence interval method, two tailed test type and .05 significance level.

4.3.1 Assessment of reflective measurement model

As outlined above, an examination of the measurement model is the first step when evaluating PLS-SEM, as different relevant criteria for reflective and formative constructs apply (Hair et al., 2019). While in formative measurement models each indicator is representing important meaning for the construct (i.e., the latent variable) and thus indicators cannot be used interchangeably or removed, as by doing so the meaning in the construct would change, indicators in reflective models show representative sets of items, which all mirror the latent variable they are measuring (Janadari et al., 2016). Thus, in reflective models the arrows in the PLS-SEM model point from the construct to the indicator. As a result, these indicators can be used interchangeably and removing one indicator from the conceptual model is possible, as long as the remaining indicators are still representative. As the underlying research model is of reflective nature, the assessment steps for reflective measurement models as outlined by Hair et al. (2019) were followed. Thus, after examining the indicator loadings and cross-loadings, the underlying research model was investigated concerning the internal reliability using Cronbach's alpha (α) and composite reliability (ρ) values. Furthermore, the average variance extracted (AVE) estimates were used to measure the convergent validity, and the HTMT as well as the Fornell-Larcker criterion were used to assess discriminant validity (Jain et al., 2022).

4.3.1.1 Construct reliability and validity

Following Hair et al. (2019) an examination of the indicator loadings was undertaken as a primary step in the reflective measurement model assessment via SMART PLS 4. According to prior research, it is urged to only include loadings of above 0.708, which serve as indicators for explaining 50% of the indicators' variances and thus yield an adequate item reliability (Hair et al., 2019). Consequently, two indicators (BI3 for the construct behavioural intention to use (BI) with a loading of 0.605, as well as C4 for the construct competence (C) with a loading of 0.335) were not considered appropriate in the initial structural model. Furthermore, the internal consistency reliability of the initial model was assessed by using composite reliability and as all values ranged from .70 to .90 they were considered "satisfactory to good" (Hair et al., 2019). Thus, none of the values proved to be problematic. Finally, also Cronbach's alpha was investigated and the value for the construct competence was found not to be satisfactory (e.g., below the threshold of .70; (Gliem & Gliem, 2003)). Therefore, due to their unsatisfying fit in the factor cross-loadings analysis, as well as the unsatisfying internal reliability, the indicators BI3 and C4 were excluded from the modified model, which was used for further investigations, even though their average variance extracted was considered appropriate. For the details on the modification process, see the data in Tables D-E in the Appendix 4.

After the extraction of the two above mentioned indicators, the construct reliability was checked again. In the adjusted model all indicators of the constructs demonstrated appropriate factor loadings (see Tables F-G in Appendix 5). Furthermore, all constructs showed acceptable Cronbach's Alpha (above .70) and composite reliability values (between .70 and .90) and the average variance extracted (AVE) did not indicate any problems (all values were above .50). The following Table 1 represents a summary of the construct reliability and validity of the model after the modification and Table 2 shows the descriptive statistics of the constructs.

Table 1 Construct reliability and validity **after modification**

Construct	α	ρ_a	ρ_c	AVE	A	BI	CI	EE	MTL	PE	R	Sc	SI
Autonomy (A)	0.795	0.816	0.865	0.616	**0.785**								
Behavioural Intention (BI)	0.879	0.880	0.943	0.892	0.501	**0.944**							
Competence (C)	0.779	0.800	0.871	0.694	0.661	0.540	**0.833**						
Effort Expectancy (EE)	0.709	0.709	0.836	0.630	0.395	0.386	0.334	**0.794**					
Motivation to learn (MTL)	0.884	0.886	0.928	0.812	0.695	0.714	0.730	0.352	**0.901**				
Performance Expectancy (PE)	0.849	0.865	0.898	0.688	0.613	0.679	0.698	0.366	0.729	**0.829**			
Relatedness (R)	0.752	0.762	0.859	0.671	0.372	0.370	0.368	0.316	0.492	0.345	**0.819**		
Scenario (Sc)					0.098	-0.011	0.168	-0.095	0.159	0.120	-0.035	**1.000**	
Social Influence (SI)	0.836	0.839	0.902	0.754	0.504	0.717	0.497	0.326	0.608	0.588	0.328	-0.068	**0.868**

Note: α = Cronbach's Alpha (.70 - .90); ρ_a =Reliability (> .70); ρ_c = Composite reliability (> .70) ; AVE = Average Variance Extracted (> .50); Scenario = Mode of L&D delivery scenario; ***AVE square root in bold***

Table 2 Descriptive statistics; overall (*N* = 144); per scenario (*N* = 72) **after modification**

Construct	*N* = 144		*N* = 72		*N* = 72	
	Mean	*SD*	Mean AI *	*SD* AI*	Mean Auto**	*SD* Auto**
Autonomy (A)	3.00	0.99	3.08	0.90	2.92	1.06
Behavioural Intention to use (BI)	3.53	1.14	3.52	1.16	3.54	1.12
Competence (C)	3.47	0.91	3.62	0.88	3.33	0.92
Effort Expectancy (EE)	3.68	0.83	3.60	0.88	3.76	0.78
Motivation to learn (MTL)	3.32	1.06	3.49	1.06	3.15	1.03
Performance Expectancy (PE)	3.62	0.92	3.72	0.88	3.51	0.95
Relatedness (R)	3.43	0.86	3.39	0.92	3.46	0.81
Social Influence (SI)	3.89	0.93	3.83	0.93	3.96	0.94

*Note: *AI = Sample of AI-guided L&D scenario only; **Auto = Sample of simple automation-based L&D scenario only; Mean = Sample Mean; SD = Standard Deviation*

Furthermore, the discriminant validity, which indicates the extent to which a construct empirically distinguishes itself form other constructs in the structural model, was assessed. In line with Henseler et al. (2015), the heterotrait-monotrait (HTMT) ratio of the correlations was used. As can be seen in Table I in Appendix 5, all values were below the proposed threshold of 0.90 as indicated by Henseler et al. (2015). Thus no discriminant validity problems were present in the underlying research and discriminant validity has been established between two reflective constructs. Finally, no issues were reported concerning the collinearity statistics for the outer model, since no VIFs > 3.3 were found, which is considered adequate (Sarstedt et al., 2021). For a comprehensive overview of all relevant matrices and tables related to the measurement model for reflective constructs, please refer to Appendix 5, specifically Tables F-J.

4.3.1.2 Model fit

Before the structural model results of PLS-SEM were investigated, the model fit was analysed. SMART PLS offers several fit measures, such as SRMR (Standardized Root Mean Square Residual), exact fit criteria (squared Euclidean distance and geodesic distance) as well as NFI (Normed Fit Index) and χ^2 (Chi-square). However, as outlined by Sarstedt et al. (2021) researchers ought to be very careful when applying these measures for PLS-SEM, as to date no thorough evaluation of these measures has been conducted. For the underlying model the SRMR, which quantifies the disparity between the actual correlation matrix and the correlation matrix implied by the model and thus serves as an absolute indicator of the goodness-of-fit criterion, was investigated (Ringle et al., 2022). According to Hu & Bentler (1999) a value less than 0.10 or 0.08 is treated as a good fit and thus the underlying model met the criteria for the saturated model with a value of 0.085, but not for the estimated model (SRMR = 0.299). The NFI criteria, which states that closer values to 1 indicate a better fit and values above 0.9 are considered acceptable, could not be fully reached by this model (NFI for the saturated model = 0.698; NFI for the estimated model = 0.522). However, I still considered the data fruitful for analysis, given the fact that PLS-SEM lacks an established goodness-of-fit measure and, according to prior research, any recommended guidelines or threshold should be regarded as highly tentative (Hair et al., 2019; Sarstedt et al., 2021). For full details on the model fit, see Table K in Appendix 5.

4.3.2 Assessment of the structural model

The second step in the two-step validation of PLS-SEM, as suggested by Hair et al. (2019) and Sarstedt et al. (2021) is the structural model assessment step. Thus, standard assessment criteria, such as collinearity, coefficient of determination (R^2), the blindfolding-based cross-validated redundancy measure (Q^2), and the statistical significance and relevance of the path coefficients were analysed (Hair et al., 2019). All relevant details concerning the following assessments of the structural model can be found in the Tables L – P in Appendix 6.

4.3.2.1 Collinearity of constructs

According to Hair et al. (2019), the structural model coefficients, which represent the relationships between constructs, are obtained by an estimation of several regression analyses. However, before an assessment of the structural relationships is possible, collinearity must be investigated in order to guarantee that it does not bias the results of the regression. Thus, the latent variable scores of the predictor constructs were used to calculate the VIF values. In line with prior research, all VIF values of the inner model were below 3, and therefore no collinearity issues among the predictor constructs were detected in the underlying research model (Hair et al., 2019; Sarstedt et al., 2021). For more details on the collinearity statistics, refer to Table L in Appendix 6.

4.3.2.2 Model's explanatory and predictive power

As no collinearity issues were present, the R^2 values (i.e., the coefficients of determination) of the endogenous constructs were assessed, as to measure the variance explained of the endogenous constructs and thus assess the model's explanatory power (Hair et al., 2019; Sarstedt et al., 2021). In other words, this reflects how much change in the dependent variables (i.e., the endogenous constructs) can be accounted for by the independent variables (i.e., the exogenous constructs). As the R^2 ranges from 0 to 1, and higher R^2 values highlight an increased explanatory power, the subsequent R^2 values of .75, .50, .25 are considered substantial, moderate, and weak (Hair et al., 2011; Henseler et al., 2009). While the R^2 values in the underlying research model for the dependent variables behavioural intention to use ($R^2 = .665$) and for motivation to learn ($R^2 = .653$) are considered moderate, the R^2 values for all other constructs were considered weak (e.g., .01 for autonomy and .03 for competence). In summary, the model explains 66.5% of the variation on behavioural intention to use and 65.3% of the variation on motivation to learn. All R^2 scores are attached in Table M in Appendix 6.

Following prior research, in addition to evaluating the R^2 values of all endogenous constructs, changes in R^2 when a given exogenous construct is excluded from the model are estimated for better estimations concerning the explanatory value of each exogenous variable in the model (i.e., how much an exogenous latent variable contributes to an endogenous latent variable's R^2 value). Thus, these changes in R^2 are referred to as effect size (f^2), which indicates the influence of each independent variable on the dependent variable (Sarstedt et al., 2021). In other words, effect size assesses the strength of relationships between latent variables. Drawing on previous research, the effect of a predictor variable at the structural level is defined as small, medium, and high with the respective values 0.02, 0.15, 0.35 (Cohen, 1988). Consequently, effect size values below 0.02 illustrate that there is no effect. The following Table 3 presenting the f-square list, shows that f-square effect size ranged from 0.001 for mode of L&D delivery scenario on relatedness to 0.272 for competence on motivation to learn and 0.233 for social influence on behavioural intention to use.

Table 3 F-square list

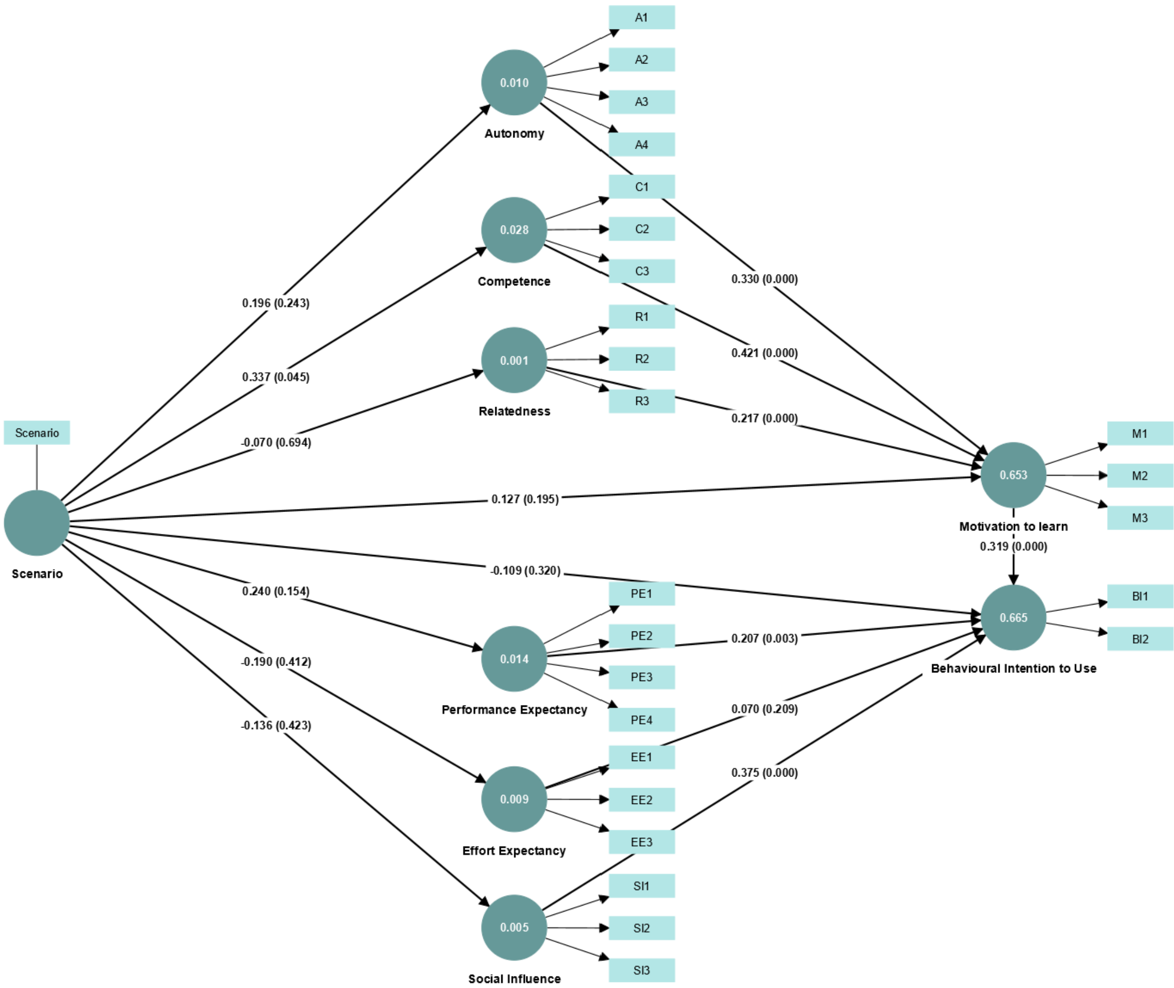
Direct Effects	**f-square**
Autonomy -> Motivation to learn	0.170
Competence -> Motivation to learn	0.272
Effort Expectancy -> Behavioural Intention to use	0.012
Motivation to learn -> Behavioural Intention to use	0.122
Performance Expectancy -> Behavioural Intention to use	0.055
Relatedness -> Motivation to learn	0.112
Scenario -> Autonomy	0.010
Scenario -> Behavioural Intention to use	0.008
Scenario -> Competence	0.029
Scenario -> Effort Expectancy	0.009
Scenario -> Motivation to learn	0.011
Scenario -> Performance Expectancy	0.015
Scenario -> Relatedness	0.001
Scenario -> Social Influence	0.005
Social Influence -> Behavioural Intention to use	0.233

Note: Scenario = mode of L&D delivery scenario; f-square = f^2

Following Shmueli et al. (2016), the PLS path model's predictive power (i.e., out-of-sample predictive power) was evaluated by using $PLS_{predict}$ procedure with k = 10, which is considered as a rule of thumb by prior researchers (Sarstedt et al., 2021). Consequently, the root mean squared error (RMSE), the mean absolute error (MAE) and Q^2 predict were investigated. While the minority of the RMSE (or MAE) values presented lower PLS-SEM prediction errors compared to the linear regression model (LM), as shown in Table O in Appendix 6, the underlying model showed low predictive power as defined by Shmueli et al. (2019). In addition, also the Q^2predict values were investigated. In the underlying research, the Q^2 values were all below 0, which indicates low predictive power, as according to Hair et al. (2019), only Q^2 values above zero for a specific reflective endogenous latent variable highlight the model's predictive relevance. For more details, see Table P in Appendix 6.

4.3.2.3 Hypothesis testing – statistical significance and relevance of path coefficients

Figure 2 Path estimates of the proposed structural model



*Note: *p-values are displayed in the brackets after the respective path coefficients (= Beta-Coefficients)*

Having analysed the model's explanatory and predictive power, Figure 2 highlights the results of the bootstrapping procedure applied to the underlying structural model in SMART PLS 4 and thus allows to assess the statistical significance and relevance of the path coefficients as outlined by Hair et al. (2019). The values of the path coefficients' significance typically range from -1 to +1 and can also be used to interpret the indirect effect of one construct on a specific target construct via one or several intervening constructs. In particular, these indirect effects are of relevance when assessing mediating effects (Nitzl, 2016). A more detailed model with all path estimates including the indicator variables can be found in Figure A in Appendix 7.

In a first step, the direct effects of the mode of L&D delivery scenario on the SDT components were tested. An investigation of the obtained path coefficients and associated p-values (as shown in Figure 2) revealed a statistically significant positive effect of the mode of L&D delivery scenario on employees' perceived competence (ß = .337, t = 2.002, p = .045). However, the effect of the scenario was not found to be significant for employees' perceived autonomy (ß = .196, t = 1.168, p = .243) nor for employees' perceived relatedness (ß = - .070, t = .393, p = .694). Concerning the structural relationships between the SDT components, the PLS-SEM results highlighted that participants' three psychological needs for self-determination significantly affected their motivation to learn. While all three variables showed similar statistical significance, thus adding support to the SDT theory, competence (ß = .421, $p < .001$) most strongly contributed to employees' motivation to learn, followed by autonomy (ß = .330, $p < .001$) and relatedness (ß = . 217, $p < .001$). Therefore, it is plausible to state that participants who are motivated to learn with AI-guided as well as simple automation-based L&D are likely to experience feelings of perceived autonomy, competence, and relatedness.

For the UTAUT constructs, it was found that neither performance expectancy (ß = .240, t = 1.426, p = .154) nor effort expectancy (ß = - .190, t = .820, p = .412) and social influence (ß = - .136, t = .800, p = .423) were statistically significantly impacted by the mode of L&D delivery scenario. However, performance expectancy (ß = .207, t = 2.972, p = .003) and social influence (ß = .375, t = 4.779, $p < .001$) significantly influenced employees' behavioural intention to use the L&D system, contrarily to effort expectancy, which did not (ß = .070, t = 1.256, p = .209). Thus, the UTAUT was only partly supported. It was found that the respective effect of social influence on behavioural intention to use was higher than all other effect sizes within the model and amounted to 0.233 – medium effect size by Cohen (1988). The effect size of performance expectancy on behavioural intention to use was 0.055 – small effect size by Cohen (1988). For all direct effects, see Table Q in Appendix 7.

In a next step, mediation analysis was performed to assess the mediating role of autonomy (A), competence (C) and relatedness (R) in the relationship between mode of L&D delivery scenario (Sc) and motivation to learn (MTL). The results (see Table 4 for the full mediation analysis results) revealed that the total effect of scenario on motivation to learn when looking at these two constructs separately was significant (**H4**: ß = .368, t = 2.104, p = .035). Thus, motivation to learn is higher in an AI-guided L&D system compared to a simple automation-based L&D system. The f^2 for this relation equals 0.035 – small effect size by Cohen (1988). With the inclusion of the mediators autonomy, competence and relatedness the direct effect of scenario on motivation to learn became not significant (ß = .127, t = 1.295, p = .195) with an f^2 value of 0.011 – no effect by Cohen (1988). However, the indirect effect of scenario on motivation to learn through competence was found significant (**H2**: ß = .142, t = 1.977, p = .048). This shows the mediating role of competence in the relationship between mode of L&D delivery scenario and motivation to learn. Hence, H2 was supported. As the indirect effect of scenario on motivation to learn through autonomy (H1: ß = .065, t = 1.096, p = .273) and the indirect effect of scenario on motivation to learn through relatedness (H3: ß = - .015, t = .371, p = .711) were not found to be significant and thus H1 and H3 were not supported, motivation to learn is almost fully mediated through competence. The strength for the effect size of competence on motivation to learn amounted to 0.272 – medium effect size by Cohen (1988).

Table 4 Mediation analysis

Total effect (H4: Sc -> MTL)			**Direct effect (Sc -> MTL)**			**Indirect Effects of Scenario on Motivation to learn**					
ß	***t***	***p***	**ß**	***t***	***p***		**ß**	***SD***	***t***	***p***	**[2.5%; 97.5%]**
						H1: Sc -> A -> MTL	0.065	0.059	1.096	0.273	- 0.038; 0.199
0.368	2.104	0.035	0.127	1.295	0.195	H2: Sc -> C -> MTL	0.142	0.072	1.977	0.048	0.006; 0.292
						H3: Sc -> R -> MTL	- 0.015	0.041	0.371	0.711	- 0.108; 0.056
Total effect (H5: Sc -> BI)			**Direct effect (Sc -> BI)**			**Indirect Effects of Scenario on Behavioural Intention to use**					
						H6: Sc -> PE -> BI	0.050	0.041	1.209	0.227	- 0.014; 0.152
- 0.068	- 0.325	0.745	- 0.109	0.994	0.320	H7: Sc -> EE -> BI	- 0.013	0.022	0.608	0.543	- 0.075; 0.014
						H8: Sc -> SI -> BI	- 0.051	0.066	0.774	0.439	- 0.193; 0.071

Note: ß = Beta-Coefficient; t = t-value; p = p-value; SD = Standard Deviation; [] = Confidence intervals bias corrected; Sc = Mode of L&D delivery scenario; MTL = Motivation to learn; A = Autonomy; C = Competence; R = Relatedness; PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; BI = Behavioural Intention to use

As with the SDT components, the mediating role of performance expectancy (PE), effort expectancy (EE) and social influence (SI) between mode of L&D delivery scenario (Sc) on behavioural intention to use (BI) was investigated. The results showed that the total effect of scenario on behavioural intention to use was not significant (H5: ß = - .068, t = - .325, p = .745). Thus, H5 was not supported. Moreover, behavioural intention to use was lower in an AI-guided L&D system compared to simple automation, but not significantly. The f^2 for the relation equals 0.008 – no effect by Cohen (1988). In sum, mode of L&D delivery scenario had no significant impact on behavioural intention to use, also all indirect effects of scenario on behavioural intention to use were found not to be significant, and thus no mediating effect of performance expectancy, effort expectancy, and social influence in the relationship between mode of L&D delivery scenario on behavioural intention to use was found. Therefore, H6, H7 and H8 were not supported.

Finally, the effect of participants' motivation to learn (MTL) as a predictor of their behavioural intention to use (BI) the L&D system was investigated. The results showed that motivation to learn was a significant factor influencing behavioural intention to use (**H9**: ß = .319, t = 4.217, $p < .001$), when comparing AI-guided L&D with simple automation-based L&D (see Figure 2). Thus, H9 was also supported. The indirect effect (see Table 5 for specific indirect effects) of scenario on behavioural intention through competence and motivation to learn was found to be marginally significant (**H10**: ß = .045, t = 1.829, p = .067). When analysing the same relationship without the mediator competence, the indirect effect becomes not significant (ß = .040, t = 1.220, p = .223). In Appendix 7, Table Q shows on overview of all direct effects, while Table R presents the individual total effects between specific variables. An overview of the structural hypothesis support can be found in Table S.

Table 5 Specific indirect effects including confidence intervals bias corrected

Specific indirect effect	ß	*M*	Bias	2.5%	97.5%	*SD*	*t*	*p*
Scenario -> R -> MTL	-0.015	-0.017	-0.002	-0.108	0.056	0.041	0.371	0.711
Scenario -> PE -> BI	0.050	0.051	0.001	-0.014	0.152	0.041	1.209	0.227
R -> MTL -> BI	0.069	0.069	0.000	0.026	0.135	0.027	2.534	0.011
C -> MTL -> BI	0.134	0.134	-0.001	0.066	0.231	0.041	3.261	0.001
A -> MTL -> BI	0.105	0.102	-0.003	0.052	0.183	0.032	3.243	0.001
Scenario -> C-> MTL -> BI	0.045	0.044	-0.001	0.007	0.109	0.025	1.829	0.067*
Scenario -> EE -> BI	-0.013	-0.016	-0.003	-0.075	0.014	0.022	0.608	0.543
Scenario -> C -> MTL	0.142	0.142	-0.000	0.006	0.292	0.072	1.977	0.048
Scenario -> A -> MTL -> BI	0.021	0.020	-0.001	-0.009	0.070	0.019	1.071	0.284
Scenario -> A -> MTL	0.065	0.064	-0.000	-0.038	0.199	0.059	1.096	0.273
Scenario -> R -> MTL -> BI	-0.005	-0.006	-0.001	-0.039	0.017	0.014	0.356	0.722
Scenario -> SI -> BI	-0.051	-0.053	-0.002	-0.193	0.071	0.066	0.774	0.439
Scenario -> MTL -> BI	0.040	0.040	-0.000	-0.015	0.117	0.033	1.220	0.223

*Note: *** marginal significance**; ß = Beta-Coefficient; M = Sample Mean; SD = Standard Deviation; t = t-value; p = p-value; Scenario = mode of L&D delivery scenario; MTL = Motivation to learn; A = Autonomy; C = Competence; R = Relatedness; PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; BI = Behavioural Intention to use*

4.3.3 Exploratory Analyses

In addition to the primary analysis, the proposed conceptual model was further developed controlling for the effects of age, gender, experience with AI-guided L&D, as well as experience with traditional human-guided L&D, on motivation to learn and behavioural intention to use. The results mostly remained the same despite the inclusion of these control variables to the initial proposed model. The only exception was the result for the indirect effect of mode of L&D delivery scenario on motivation to learn through competence which now became just marginally significant ($ß = .140$, $t = 1.955$, $p = .051$). The analysis shows then that gender, age and experience with human-guided L&D did not significantly impact motivation to learn or behavioural intention to use, while experience with AI-guided L&D had a statistically significant positive impact on participants' motivation to learn ($ß = .120$, $t = 2.615$, $p = .009$). Further, no significant effect was found for the relationship between experience with AI-guided L&D and behavioural intention to use ($ß = - .057$, $t = 0.910$, $p = .363$). In Appendix 8, Figure B represents the structural model including control variables with path coefficients and p-values, and Table T and U show the respective direct and indirect effects of the exploratory analyses.

5 Discussion

The underlying research aimed at investigating AI-guided and simple automation-based employee learning and development and its impacts on employees' motivation to learn by referring to the Self-determination Theory (SDT) and the Unified Theory of Acceptance and Use of Technology (UTAUT). PLS-SEM was applied as the statistical method to explore the structural relationships between the variables. The research model assessed whether AI's potential to create personalized adaptive learning experiences satisfies employees' needs for autonomy, competence and relatedness (e.g., self-determination) more, and thus increases their motivation to learn compared to simple automation-based L&D. Furthermore, it was tested whether learners' performance expectancy, effort expectancy and social influence is increased by AI-guided L&D systems compared to simple automation-based systems, and how this impacts learners' behavioural intention to use a L&D system. Finally, the research model investigated the relationship between motivation to learn and behavioural intention to use.

The results revealed that AI-guided L&D significantly and positively impacts motivation to learn compared to simple automation-based L&D and thus **H4** of this research was supported.

In fact, AI-guided L&D accounts for 65.3% of the variance in motivation to learn. Interestingly, however, the increase in motivation can be attributed almost entirely to the increased perceived competence of learners in AI-guided L&D compared to a simple automation-based system. Thus, it was found that AI-guided L&D impacts learners' perception of competence, which then in turn significantly impacts their motivation to learn. Thus, **H2**, in terms of the mediating role of perceived competence between the mode of L&D delivery scenario and motivation to learn was supported. This finding is in line with previous research which suggests that providing learners with meaningful learning options and challenges tailored to their skill level and learning style, giving personalized feedback and assistance, and thus also suggesting an appropriate effective methodology enhances feelings of competence (Alamri et al., 2020; Deci & Ryan, 1985; Garn & Jolly, 2014; Kashive et al., 2021). Thus, AI's potential to provide learners with more competence in terms of offering a customized learning experience and progress tracking, as outlined by prior research (Crossley et al., 2016; Kashive et al., 2021), is highlighted by the findings of the underlying research model.

No mediating role, however, was found for the remaining SDT components autonomy and relatedness, as learners' feelings of autonomy and relatedness were not significantly increased in AI-guided L&D compared to simple automation-based L&D. Thus, H1 and H3 were not supported. These findings are contrary to findings of prior researchers who highlighted that personalized opportunities and choices, as well as appropriate course programs, will lead to an autonomy supportive environment (Deci & Ryan, 2000; Lee et al., 2015; Patall et al., 2010) and that personalized learning components (e.g., personalized learning pathways, personalized readings, and personalized feedback), which are also present in AI-guided learning, are the main determinants of learners' perceived autonomy and competence (Alamri et al., 2020). However, the lack of relatedness in such personalized courses was already investigated by researchers, who mentioned that learners lacked relatedness to their peers (i.e., the other learners) in both personalized and one-size-fits all online courses (Alamri et al., 2020). Furthermore, the findings resonate with Garn & Jolly (2014), who found that aligning personal learning interests within the learning program will enhance both learners' feelings of relatedness and competence, while this study found competence to be positively impacted by a learning modus that is more personalizable. What the findings of this study and also of prior research show, is that the level of need satisfaction is greatly impacted by the context in which an activity happens, which provides an explanation, of why some needs are (more) satisfied in an AI-guided L&D system opposed to a simple automation-based delivery mode. Thus, as already outlined by prior academic work, findings regarding the satisfaction of these three psychological needs are not definite and vary depending on the context (Deci & Ryan, 2000; Roca & Gagné, 2008).

However, previous studies on the SDT model posited that all three psychological needs enhance intrinsic motivation (Deci & Ryan, 2000; Hsu, 2021). My research findings corroborate these findings, as perceived autonomy, perceived competence, as well as perceived relatedness significantly impacted individuals' motivation to learn irrespective of the mode of L&D delivery. Thus, if individuals are self-determined in their behaviour and therefore autonomously motivated, their (intrinsic) motivation to learn is increased.

In terms of learners' acceptance of AI-guided or simple automation-based L&D, results of the PLS-SEM analysis showed that none of the UTAUT constructs (i.e., performance expectancy, effort expectancy, and social influence) was significantly impacted by the mode of L&D delivery. Moreover, the results revealed that the impacts of AI-guided L&D and simple-automation-based learning on behavioural intentions to use did not differ from each other. Thus, H5 of the research model was not supported. Moreover, performance expectancy, effort expectancy, and social influence did not act as mediators in the relationship between mode of L&D delivery and behavioural intention to use. Consequently, H6, H7 and H8 of this research model were also not supported. This may be because the scenarios, even though thoroughly backed by prior literature on AI-guided and simple automation-based L&D systems, still were artificially drawn up and some participants might have had difficulties imagining themselves in the outlined situation and found it difficult to connect the scenarios to their real work environment, in which performance expectancy, effort expectancy, and social influence are relevant. In this regard, it might have been beneficial for this research to empirically test the theoretical model of artificially intelligent device use acceptance (AIDUA) as proposed by Gursoy et al. (2019) which is specifically tailored to the multi-faceted role of AI devices used in customer interactions. In particular, given that the traditional technology acceptance models, such as TAM and UTAUT, were initially created to explore the adoption of non-intelligent technologies, and thus did not take into account AI's humanlike intelligence, which would make the ease-of-use and the perceived-usefulness construct irrelevant (Lu et al., 2019), this model might have been a better fit with the AI-guided L&D scenario, as it suggests a three-step acceptance generation process which determines whether users accept the use of AI devices during their service interactions or whether they object it. However, as the underlying study also aimed at investigating and comparing the impacts of simple automation (i.e., non-intelligent technology), which it would not fit with, the UTAUT was chosen instead of the AIDUA model.

Regardless of the insignificant impact of the L&D delivery mode on the individual UTAUT constructs, it was possible to partially verify the UTAUT theory as proposed by Venkatesh et al. (2003), as both performance expectancy as well as social influence significantly impacted individuals' behavioural intention to use. However, no such significant effect was found for effort expectancy. These results are in contrast to findings of Lin et al. (2022) who used an extended version of the UTAUT and found that effort expectancy and social influence significantly impacted adoption behaviour, while performance expectancy was not a significant predictor of usage intentions. These findings are also supported by Hsu (2021) who found effort expectancy and social influence to be significant for predicting use intentions of LMOOCs, while performance expectancy was not significant. Again, others found that social influence is a positive predictor of students' behavioural intention to use empathic AI-based technologies in an educational forum, while performance expectancy and effort expectancy were considered irrelevant for the learners (Isaias et al., 2017). The findings of the underlying research are also contrary to findings of Jain et al. (2022) and Kwan et al. (2019), which in line with the initial UTAUT theory (Venkatesh et al., 2003), found a significant positive impact for all constructs (e.g. performance expectancy, effort expectancy and social influence) on individuals' behavioural intention to use AI-enabled tools for collaboration (Jain et al., 2022) and e-HRM (Kwan et al., 2019).

These different findings of the underlying research compared to prior research again highlight that the variables' predictability is not definite, and variations occur given the underlying context in which they are used as outlined by previous research (Devolder et al., 2012).

Finally, the relationship between individuals' self-determined motivation to learn and their technology acceptance was investigated. The results of the PLS-SEM analysis revealed that people's behavioural intention to actually use a L&D system is significantly positively impacted by their motivation to learn, when comparing AI-guided L&D with simple automation-based L&D. Thus, **H9** of this research was also supported. Interestingly however, it was found that the mode of L&D delivery had no significant direct impact on motivation to learn. Instead, the relationship between the mode of L&D delivery and motivation to learn is fully mediated through competence, meaning that an increase in perceived competence leads to an increase in people's motivation to learn, which then in turn drives their behavioural intention to use the L&D system. Thus, the indirect effect of the mode of L&D delivery on behavioural intention to use through competence and motivation to learn was marginally significant, which resulted in a marginal support for **H10** in the underlying research. The finding that motivation to learn is a significant factor for increasing use intentions is opposed to findings of Hsu (2021) and Sun & Gao (2020), who found that motivation to learn did not serve as a significant predictor for behavioural intention to use, even though Hsu (2021) found motivation to significantly impact use behaviour (i.e. actual usage; which was not investigated in this research). They reason that learner's motivation has more influence on actual use behaviour than just their intention (i.e., intention to engage with it). The results of the underlying analysis however, go in the opposite direction and suggest that motivation is indeed influential to their intention. This finding is also echoed by Chiu & Wang (2008) who found that intrinsic motivation (i.e., self-determination) is a significant factor driving learners' intentions to continuously use web-based learning. Similarly, also Yoo et al. (2012) highlighted in their findings the significant role of intrinsic motivators on employees' intentions to use e-learning in the workplace. However, they considered effort expectancy, attitudes, and anxiety as intrinsic motivators, while performance expectancy, social influence, and facilitating conditions were mentioned as extrinsically motivating factors. Given these diverse findings, it is thus possible that intrinsic motivation, which was investigated in the underlying study by referring to the Self-determination Theory, has different effects on use intentions compared to extrinsic motivational factors. Thus, it would be interesting for future research to further explore the role of extrinsic motivation in technology acceptance.

5.1 Implications for theory

First, this research contributes to the emerging literature on AI-technology in a learning and development context. It builds on past empirical and conceptual studies that have investigated the potential of AI-enabled L&D in classroom settings (Kabudi et al., 2021), but also within a business context (Bhatt & Shah, 2023; Bhatt & Muduli, 2022; Chen, 2022). As prior scholars found AI in L&D to be beneficial not only for learners, but also for instructors, educational institutions, and businesses, this research further investigated the main drivers of technology adoption in a work context. Thus, this research allows for a better understanding of the distinct characteristics of AI-guided L&D in comparison to simple automation-based L&D, which has not been clearly defined yet in prior academic work, in particular regarding employee L&D.

Second, by building on prior findings on technology adoption (Davis, 1989), which in past decades mostly focused on technology adoption in online language learning (e.g., MOOCs (Hsu, 2021), AI-enabled language learning (Lin et al., 2022)), with participants mostly being students, this research extends the current literature by applying the Unified Theory of Acceptance and Use of Technology in an organizational L&D setting. Even though this study did not investigate actual usage behaviour as observed in other studies (Hsu, 2021; Jain et al., 2022) due to time and resource constraints, the underlying study still provides beneficial insights for theorists and practitioners alike concerning people's use intentions, which then can be used to predict real usage. This is also supported by prior research and the original UTAUT model (Venkatesh et al., 2003), which highlight that individuals first are willing to engage with a new technology, before they actually use it. The findings revealed that there are no significant differences between AI-enabled and simple automation-based L&D settings in terms of learners' behavioural intention to use an L&D system, as the L&D delivery scenario did not significantly impact behavioural intention to use when comparing AI-guided L&D with simple automation-based L&D. Furthermore, performance expectancy, effort expectancy, and social influence were not significantly impacted by the mode of L&D delivery. However, performance expectancy and social influence positively impacted learners' behavioural intentions to use, while effort expectancy was not found significant in this relationship, thus arriving at different findings than the original UTAUT model (Venkatesh et al., 2003), where all three constructs significantly impacted behavioural intention to use. Thus, this research contributes to the existing findings of the UTAUT and highlights once more that the variables' predictabilities are not definite and their impacts vary depending on the context (Devolder et al., 2012).

Third, this research builds on previous findings of one of the most thorough motivational theories – the Self-determination Theory – which has since its introduction by Deci (1971) been studied and applied by many scholars (Van den Broeck et al., 2021). The findings of this research extend the existing research, which has concluded that learners' motivation is an important factor to consider in L&D contexts (Kashive et al., 2021; Wang et al., 2019). In fact, learners' increased perceived competence due to AI-guided L&D compared to simple automation-based L&D is a main driver for increased motivation to learn. Thus, it was not only found that AI leads to an increase in motivation to learn compared to simple automation, but that perceived competence fully mediates this effect, suggesting that no other component is needed to explain the total effect of AI-guided L&D on motivation to learn. In addition to this main finding, this empirical research also adds to the evidence supporting the SDT in general, as all three psychological needs significantly increased learners' motivation (Deci & Ryan, 2000).

Overall, the conceptual model develops a comprehensive framework to better understand the usage intentions of AI-guided L&D systems compared to systems operated by simple automation and particularly highlights the vital role of motivation within L&D systems as the findings also revealed that motivation to learn is a significant predictor of learners' use intentions. While the mode of L&D delivery scenario had no significant impact on the individual UTAUT constructs, which then did not mediate the relationship between the L&D delivery mode and behavioural intention to use, it was however found that the delivery mode impacts motivation to learn through increased perceived competence, which then significantly impacts behavioural intention to use. Thus, the findings corroborate prior research that combined technology acceptance and SDT and also arrived at the result that intrinsic motivation (expressed through the three psychological needs) impacts use intentions (Chiu & Wang, 2008; Osei et al., 2022). However, the role of extrinsic motivation within this constellation remains unclear and thus it implies that despite these positive findings concerning learners' increased intrinsic motivation and subsequent use intentions, further research in this regard is needed.

Lastly, this research also adds to the existing literature on AI aversion and trust in AI, which as outlined by prior research, is a crucial determinant impacting the adoption and use of AI-enabled tools (Jain et al., 2022). In fact, algorithmic aversion is defined as the phenomenon in which individuals consciously or unconsciously are reluctant to follow algorithmic advice and prefer human experts' decisions, even though AI technology in decision-making tends to be more efficient and its performance often times is superior compared to humans' capabilities (Mahmud et al., 2022). While prior studies highlighted the existence of AI aversion in regard to using AI systems in HR practices (Bhatt & Shah, 2023), the underlying research speaks against that as it is shown that employees' motivation to learn through increased perceived competence indirectly increases also their intention to use a L&D system, when being guided by an algorithm compared to simple automation, where decisions are taken by an HR manager. Thus, suggesting learners will trust and accept the decisions and the advice provided by AI-enabled tools.

5.2 Implications for practitioners

In addition, this research offers various practical implications. The findings on the SDT of the proposed conceptual model enable practitioners to investigate and understand the drivers behind employees' motivations to continuously learn with new L&D technology, such as AI-guided L&D systems. Moreover, the findings on the UTAUT provide organizations with valuable information in terms of successful technology implementation as it presents a holistic view on individuals' usage intentions of new information technology.

First, practitioners (e.g., HR managers) receive valuable insights from a Self-determination Theory perspective regarding the driving factors of employees' motivation to learn. Thus, this allows them to explore, which motivational aspects employees are looking for in L&D initiatives and whether the new technology is able to satisfy their three psychological needs for autonomy, competence and relatedness which allow them to engage in an learning initiative autonomously motivated. Thus, it is again highlighted that having a well-designed L&D program in place is not only critical for organizational success (Naim, 2023), but also for retaining and motivating top talent (Chen, 2014). This becomes even more relevant considering the great resignation and the accompanying voluntary retirements of employees, which shifted the power in the workplace from the employer to the employees, who are demanding not only flexibility and autonomy (Gagné et al., 2022), but also expect seamless, intuitive, and personalized L&D initiatives (Maity, 2019). Consequently, it is essential for companies and managers alike to provide development opportunities, which target the right employees with relevant need-tailored content and thus boost not only employees' skills and abilities, but also increase their motivation and satisfaction levels. As shown by the findings of this research, AI-guided L&D significantly increases learners' motivation to learn and is thus a beneficial investment for practitioners. It is shown however that this effect happens almost fully through the increased perceived competence due to AI-guided L&D compared to simple automation-based L&D. Thus, this research suggests that customized learning experiences (e.g., courses, tasks and challenges tailored specifically to individual skill levels and capabilities) along with consistent and personalized feedback on their performance (Alamri et al., 2020), which all contribute to individuals' increased perceived competence, are important for increasing motivation to learn. In this regard, HR practitioners should be aware of AI's capabilities, as it can not only facilitate learning by providing an adequate pace of learning and personal assistance, dependent on employees' individual learning style, but also offers learners a suitable effective methodology and allows for self-evaluation (Kashive et al., 2021). Thus, when HR practitioners employ AI-enabled L&D, they can track employees' progress incrementally via log-files and click-stream analyses (Crossley et al., 2016).

Second, as the mode of L&D delivery had no significant impact on the individual UTAUT constructs, which then did not mediate the relationship between L&D delivery mode and behavioural intention to use, it is shown that employees' performance expectancy, effort expectancy, and social influence do not differ for AI-guided and simple automation-based L&D. However, it is suggested that investments in AI-guided L&D compared to simple automation- based L&D can indirectly increase learners' use intentions, when employees are self-determined motivated, as this research found that the delivery mode impacts motivation to learn through increased perceived competence, which then significantly impacts behavioural intention to use. Thus, as suggested above, providing customized learning experiences and personalized feedback (Alamri et al., 2020), to increase individuals' perceived competence, are even more important, as they will not only increase learners' motivation, but also their intentions.

Third, despite the non-significant direct relationship between L&D delivery mode and behavioural intention to use, organizations who strive to implement L&D for their employees should be cautious of performance expectancy and social influence, as they are crucial antecedents impacting the behavioural intention to use, regardless the mode of L&D delivery. As such, it becomes relevant for managers to understand the capabilities of AI-guided and simple automation-based systems and their impact on employees' performance, as employees might only intend to use the new technology when their expectations are met. Furthermore, given the significant positive impact of social influence on use intention, it becomes vital for managers to acknowledge that some employees might only accept the new technology if they are influenced by their peers or supervisors. Thus, as outlined by prior research, existing and prior users of the new technology, as well as supervisors and top management can influence others' willingness to engage with it (Alexander et al., 2018; Jain et al., 2022; Mahmud et al., 2022; Zhang et al., 2021). This is in particular relevant, given AI's role as an actor within a work system, which outlines that employees, developers and managers a like need to collaborate for a successful AI integration (Anthony et al., 2023).

For human resource managers this study further revealed that if individuals already had experience with AI-guided L&D, their motivation to learn is increased significantly compared to individuals who did not yet have experience with AI-guided L&D. Further analysis of the proposed conceptual model thus suggest that it is essential for HR departments and their managers to start implementing AI-guided L&D step by step, as motivational levels are likely to increase, once the employees have had a first touchpoint with such L&D systems. Moreover, as suggested by Bauer et al. (2016), the implementation of L&D strategies which aim at boosting leaners' motivation to learn can contribute to positive learning outcomes and the successful application of critical skills in the work setting. Therefore, this finding suggests that the mode of L&D delivery may indirectly also impact employees' motivation to work in general.

Finally, it can be concluded that AI technology in employees' L&D is beneficial for both, the individual and the organization and given its great potential to bring human resource management to the next level this research also suggests that HR practitioners should prioritize investment in AI technology (Chen, 2022). In particular, practitioners should be encouraged by the findings of this study to bring in the algorithms, as it is shown that employees are more motivated and indirectly also intent to use a L&D system more, when being guided by AI compared to simple automation, and thus the often times discussed aversion towards AI-enabled tools seems to be not present in this case (Mahmud et al., 2022).

5.3 Limitations and future research

While this research has important theoretical and practical implications, some limitations in this work should be addressed in future research. First, most of the data was collected through a non-probability sampling technique, which given the time and resource constraints was a reasonable technique, but however led to a non-representative sample (Vehovar et al., 2016). Specifically, most of the participants were contacted personally via an anonymous Qualtrics link via WhatsApp, which led to the result that most of the participants originated from Europe, and particularly from Austria. Thus, it is suggested that this research is replicated with a larger and more diverse sample to improve the reliability of the findings.

Furthermore, given the fact that the underlying study used a self-report questionnaire, some of the participants might not have answered honestly to the questions, which might have led to biased responses (McGrath et al., 2010) and hence limits the generalizability of the results.

Moreover, the study was conducted within a short period of time and as people's experiences with technology are likely to change when they gain more knowledge and experience, a longitudinal approach examining technology usage behaviour as also suggested by Jain et al., (2022) could provide further insights into employees' technology adoption and on how these findings are rather stable or rather volatile and thus easily change with changing context.

Another limitation of this research arises in terms of the research's external validity. Even though the outlined scenarios for AI-guided and simple automation-based L&D in a work context were thoroughly backed by prior academic work and relevant findings, participants were required to imagine themselves in the outlined scenario and provide answers based on how they would potentially feel and act in the described situation. Even though such an approach is commonly used to predict actual behaviour, differences regarding actual use behaviour might exist (Ajzen & Gilbert Cote, 2008), different participants may imagine slightly different scenarios and might do so with differing levels of fluency (Alter et al., 2007; Kühl & Eitel, 2016). Hence, future research should not only test the proposed research model in a hypothetical model as this research did, but rather investigate employees' use intentions and motivation to learn in an actual work setting, e.g., a company, which is planning to implement AI-guided L&D. Consequently, in future studies, not only employees' use intentions, but also their actual use behaviour can be investigated and thus all variables of the initial UTAUT model (e.g., facilitating condition), which were left out of this research can be included (Venkatesh et al., 2003). As such, future studies could also test whether motivation to learn also impacts actual use behaviour in an AI-guided L&D system compared to a simple automation-based system. Thus, AI-guided L&D compared to simple automation-based L&D could also be tested with the UTAUT2 in connection with the SDT as proposed by Osei et al. (2022), in order to also investigate variables that are related to actual usage, such as price value and habit.

Applying the proposed research model in an actual work context, could potentially also lead to different results concerning the impact of AI-guided L&D on the individual UTAUT and SDT components. While this study only found competence to be significantly impacted by the AI-guided L&D compared to simple automation, future studies applied in a real-life work-setting might be able to find more mediators in the relationship between mode of L&D delivery and motivation to learn as well as use intentions. This is because participants then don't need to imagine themselves in the described scenarios, but are actually working with the underlying L&D systems in their day-to-day business.

As can be seen from the above outlined limitations, from a theoretical perspective, there are several research directions to be taken, and further questions regarding the relationship between the SDT and the UTAUT remain for future research. In particular, future studies could also look into how AI aversion mediates the relationship between individuals' motivation to learn and their intention to use the system. In addition, as previously highlighted in the discussion, the role of extrinsic motivation in the proposed research model needs to be further investigated. Future studies could also test AI-guided learning and development specifically with the theoretical model of artificially intelligent (AI) device use acceptance (AIDUA) as proposed by Gursoy et al. (2019) to further investigate employees' willingness to accept the use of AI devices or their objection of them. Moreover, different aspects of an AI-guided system can impact many behavioural and attitudinal variables, due to for example different levels of anthropomorphism of AI-technologies (i.e., people's perceptions of AI-enabled technology (AIET) as humanlike) (Li & Suh, 2021; Moussawi et al., 2021). As such, these different anthropomorphism levels might have influenced the results of this study by having participants within the described scenario with a completely different perception than others in the same scenario, thus leading to opposed responses and therefore no differences. Consequently, it would be interesting to study how more or less anthropomorphism impacts the variables within the proposed conceptual model. Indeed, higher levels of anthropomorphism could potentially lead to higher levels of relatedness, as learners would perceive the AI-technology as more humanlike and social (Jiang et al., 2022; Morana et al., 2020). Thus, the "human-touch" would not be missing as much (Bhatt & Shah, 2023), as meaningful relationships could be built due to smoother and socially embedded interactions (Roesler et al., 2022).

Finally, it would have also been interesting to not only compare AI-guided L&D with simple-automation based L&D, but also with a third condition representing full human-based learning without any technology. Future research could employ this third condition in the proposed research model and investigate, whether AI-guided or simple automation-based L&D approximate more to the human-led L&D and compare all three conditions with each other.

6 Conclusion

This empirical research and the underlying conceptual model attempt to develop a comprehensive framework to investigate the impacts of AI-guided L&D compared to simple automation-based L&D on learners' motivation to learn and their behavioural intention to use the L&D system in a work context. In regard to learners' use intentions based on the UTAUT model, no significant direct impact of AI-guided L&D compared to simple automation-based L&D was found. However, performance expectancy, as well as social influence, emerged as significant predictors of behavioural intention to use in both L&D delivery modes. Thus, practitioners should focus on developing a positive social influence and be cautious of employees' performance expectations when designing and implementing L&D initiatives in order to increase technology acceptance.

From a Self-determination Theory perspective, the findings further revealed AI's potential to significantly increase motivation to learn compared to simple automation-based applications. In fact, this research provides a first explanation of why AI-guided solutions lead to an increase in employees' motivation to learn as the results of the study revealed that the relationship between the mode of L&D delivery and motivation to learn is fully mediated through competence. Thus, it was found that an increase in perceived competence due to an AI-guided L&D system compared to a simple automation-based system leads to an increase in people's motivation to learn, which then in turn drives their behavioural intention to use the L&D system. Thus, this research highlights the importance of feedback along with providing customized learning experiences which are aligned with individual learning styles, learners' characteristics as well as skill levels and capabilities in an L&D context in order to increase employees' perceived competence and thus self-determination. As a result, practitioners ought to invest in new technology which is capable of providing these features and should be aware of AI's potential to provide a seamless, intuitive and personalized learning experience, which employees are striving for nowadays. Overall, this research thus supports the assumption that the use of AI in employee L&D drives autonomous motivation to learn through self-determination more than simple automation-based L&D.

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Appendices

Appendix 1: Qualtrics Survey

Informed Consent

Dear participant,
first of all, welcome and thank you in advance for your participation in this dissertation research project. My name is Tanja Reitgruber and I am currently developing my **Master's Thesis on the topic of Automation and the Future of Work**. The goal of this survey is to understand how individuals feel about guidance in Learning & Development (L&D) processes.

This survey is expected to take approximately 5-10 minutes and it is advisable to answer this survey all at once without interruptions. Your responses will be anonymous and confidential and will only be used for research in the scope of my master's thesis. Your participation is voluntary. You have the right to decline to participate and to withdraw once participation has begun. To do so, simply close this web page. There are no foreseeable consequences of participating, declining, or withdrawing from this study.

If you have any questions regarding this study, please contact me, Tanja Reitgruber, via my email address **s-treitgruber@ucp.pt.**

Do you consent to participate in this study?

o I consent
o I do not consent

Q: Thank you for agreeing to answer this survey.

You will now be presented with the following scenario. Please read it attentively and imagine yourself in it.

When the minimum reading time for the scenario has passed, the progress button will appear and you can move forward to the next question.

You are an **employee of company X**, which is using **automated (technology-enhanced) learning and development (L&D)** to train its employees. The company uses a **learning management system (LMS)** to manage its L&D activities. As such, the LMS enables the streamlining of administrative work, and thus allocates courses, instructors, and employees to respective training initiatives.

The LMS platform provides you fixed bundles of interactive online modules that you can complete at your own pace, anytime, and everywhere. Each module can include instructional videos, interactive simulations, and quizzes to test your knowledge. Moreover, automated feedback mechanisms can be built into the training modules, such as chatbots or virtual assistants.

Furthermore, the LMS tracks your progress and provides managers with reports on your achievement rates and quiz scores, analyses development gaps and recommends appropriate courses. By automating the employee L&D process, the company can make sure that all employees receive constant training and that everyone can access the L&D materials whenever needed.

The HR expert is responsible for tracking your learning progress, identifying employees who are having difficulties with the L&D program and providing additional help. Finally, the HR expert analyses the effectiveness of the L&D program and makes any required changes or revisions.

Scenario 1: Simple automation based L&D

Imagine now, that company X uses **simple automation in its LMS**. This means that **some tasks previously performed by an HR manager, are now operated by simple automation**. To your better understanding, compared to Artificial Intelligence (AI), which enables a computer system to learn from its errors and adjust to new inputs, simple automation follows automated rules, thus does not adjust itself and has a specific focus on replacing human resources in repetitive workflows.

In summary, an **automated L&D system**:

- aids your training needs, by listing existing courses based on pre-prepared educational materials
- shows you an overview of your learning progress during the L&D program
- includes automated chatbots for communication, which use pre-programmed messages
- cannot provide feedback on your learning journey and intelligently recommend programs tailored to your cognitive and socio-emotional needs
- cannot make decisions regarding your L&D journey
- is programmed once by the developing team and remains the same forever unless a programmer re-programs it

Please make an effort to imagine yourself in the described situation and answer the following questions as realistically as possible.
Thank you!

Manipulation-Check Question - Scenario 1

Q: According to what you have just read above, who guides you through the LMS platform and decides which learning initiative you should take and adapts your learning journey accordingly?

o An automated system
o An AI automated system

When the wrong answer was provided:

You answered that an **AI automated system** guides you through the LMS platform. However, the described system is a **simple automated** LMS. This means that it is not able to learn by itself about the employee and does not adapt itself to employees' needs. The learning journey is predefined within a simple automated LMS.

When the correct answer was provided:

Yes, it is the case, that an **automated system** guides you through the LMS platform in the outlined situation. This means that it is not able to learn by itself about the employee and does not adapt itself to employees' needs. The learning journey is predefined within a simple automated LMS.

Scenario 2: AI-guided L&D

Imagine now, that company X uses **Artificial Intelligence (AI) in its LMS**. This means that **all tasks previously performed by an HR manager, are now operated by AI**. To your better understanding, compared to simple automation, which follows automated rules, thus does not adjust itself and has a specific focus on replacing human resources in repetitive workflows, AI enables a computer system to learn from its errors and adjust to new inputs.

In summary, an **AI automated L&D system**:

- aids your training needs, by assessing your training needs and suggesting suitable courses based on employee-tailored educational materials
- scans and monitors your learning status, emotional status and teaching pace
- includes AI chatbots for communication, which use messages unique to each interaction
- can provide feedback on your learning journey and intelligently recommend programs tailored to your cognitive and socio-emotional needs
- can make decisions regarding your L&D journey
- is programmed once by the developing team and ever changing thereafter, as the AI program re-programs itself, taking that decision by itself

Please make an effort to imagine yourself in the described situation and answer the following questions as realistically as possible.
Thank you!

Manipulation-Check Question - Scenario 2

Q: According to what you have just read above, who guides you through the LMS platform and decides which learning initiative you should take and adapts your learning journey accordingly?

o An automated system
o An AI automated system

When the wrong answer was provided:

You answered that an **automated system** guides you through the LMS platform. However, the described system is an **AI automated** LMS. This means that it is able to learn by itself about the employee and adapts to employees' needs. The learning journey is adaptable within an AI automated LMS.

When the correct answer was provided:

Yes, it is the case, that an **AI automated system** guides you through the LMS platform in the outlined situation. This means that it is able to learn by itself about the employee and adapts to employees' needs. The learning journey is adaptable within an AI automated LMS.

Questions to the SDT constructs

Q: Please indicate your agreement with the following statements keeping in mind that you are participating in simple automation-based (AI-guided*) L&D at your company.

Autonomy (A) (Cronbach's α = .795)	Not at all true (1)	Slightly untrue (2)	Neither untrue nor true (3)	Slightly true (4)	Very true (5)
A1. I would be able to decide my own learning process in this L&D program.	O	O	O	O	O
A2. I feel very strongly that the way I would use this L&D program for learning would fit perfectly the way I prefer to learn.	O	O	O	O	O
A3. I feel that the way I would learn via this L&D program would definitely be an expression of myself.	O	O	O	O	O
A4. I agree that I would have the opportunity to make choices with respect to the way I would learn via this L&D program.	O	O	O	O	O

*Note: * depending on the scenario, either simple automation-based L&D or AI-guided L&D was stated in the question*

Competence (C) (Cronbach's α = .695)	Not at all true (1)	Slightly untrue (2)	Neither untrue nor true (3)	Slightly true (4)	Very true (5)
C1. I feel that with this L&D program I would make a huge progress with respect to the end result I pursue.	O	O	O	O	O
C2. I feel that I would learn very effectively with this L&D program.	O	O	O	O	O
C3. I feel that learning via this L&D program would be a way of learning in which I would do very well.	O	O	O	O	O
C4. I feel that I would be able to manage with the requirements of this L&D program which I would be enrolled in.	O	O	O	O	O

Relatedness (R) (Cronbach's α = .752)	Not at all true (1)	Slightly untrue (2)	Neither untrue nor true (3)	Slightly true (4)	Very true (5)
R1. I would feel extremely comfortable when being with the other participants of this L&D program.	O	O	O	O	O
R2. I feel that I would associate with the other participants of this L&D program in a very friendly way.	O	O	O	O	O
R3. I feel communicating with the other participants of this L&D program would be smooth and successful.	O	O	O	O	O

Motivation to learn (MTL) (Cronbach's α = .884)	Not at all true (1)	Slightly untrue (2)	Neither untrue nor true (3)	Slightly true (4)	Very true (5)
MTL1. I would enjoy learning with this L&D program very much.	O	O	O	O	O
MTL2. I would describe learning with this L&D program as very interesting.	O	O	O	O	O
MTL3. I think learning with this L&D program would be quite enjoyable.	O	O	O	O	O

Attention-Check Question

Q: So I can make sure you read this question carefully, please select "Agree".
o Strongly disagree (1)
o Disagree (2)
o Neither agree nor disagree (3)
o Agree (4)
o Strongly agree (5)

Questions to the UTAUT constructs

Q: Now again, please indicate your agreement with the following statements. Keep in mind that you are participating in simple automation-based (AI guided*) L&D at your company.

Performance Expectancy (PE) (Cronbach's α = .849)	Not at all true (1)	Slightly untrue (2)	Neither untrue nor true (3)	Slightly true (4)	Very true (5)
PE1. I would find this L&D program to be useful for my professional development.	O	O	O	O	O
PE2. Using this L&D program would enable me to complete learning tasks more quickly.	O	O	O	O	O
PE3. Using this L&D program would increase my learning productivity.	O	O	O	O	O
PE4. Using this L&D program would improve my performance.	O	O	O	O	O

*Note: * depending on the scenario, either simple automation-based L&D or AI-guided L&D was stated in the question*

Effort Expectancy (EE) (Cronbach's α = .709)	Not at all true (1)	Slightly untrue (2)	Neither untrue nor true (3)	Slightly true (4)	Very true (5)
EE1. I would find this L&D program flexible and easy to use.	O	O	O	O	O
EE2. Learning to use this L&D program for learning would not require much effort.	O	O	O	O	O
EE3. It would be easy for me to become skillful at using this L&D program.	O	O	O	O	O

Social Influence (SI) (Cronbach's α = .836)	Not at all true (1)	Slightly untrue (2)	Neither untrue nor true (3)	Slightly true (4)	Very true (5)
SI1. I would use this L&D program for learning if my supervisor recommended it to me.	O	O	O	O	O
SI2. I would like to use this L&D program for learning if my supervisor supported the use of it.	O	O	O	O	O
SI3. I would use this L&D program if the supervisors of my department are helpful in the use of this L&D program.	O	O	O	O	O

Q: Keeping in mind the answers to the previous statements, what are your intentions concerning this simple automation-based (AI guided*) L&D program?

Behavioural Intention to Use (BI) (Cronbach's α = .759)	Not at all true (1)	Slightly untrue (2)	Neither untrue nor true (3)	Slightly true (4)	Very true (5)
BI1. If my workplace offers this possibility, I plan to use this L&D program for learning.	O	O	O	O	O
BI2. If my workplace offers this possibility, I think I will use this L&D program for learning frequently.	O	O	O	O	O
BI3. If my workplace offers this possibility, I would prefer it to a usual human led L&D program.	O	O	O	O	O

*Note: * depending on the scenario, either simple automation-based L&D or AI-guided L&D was stated in the question*

Final questions

Q: Answering the questions of this study was...

o Extremely difficult (1)
o Moderately difficult (2)
o Slightly difficult (3)
o Neither easy nor difficult (4)
o Slightly easy (5)
o Moderately easy (6)
o Extremely easy (7)

Q: Imagining the previously described scenario was...
o Extremely difficult (1)
o Moderately difficult (2)
o Slightly difficult (3)
o Neither easy nor difficult (4)
o Slightly easy (5)
o Moderately easy (6)
o Extremely easy (7)

Q: How do you assess your understanding of the following concepts?

Concept	Extremely bad (1)	Bad (2)	Neither good nor bad (3)	Good (4)	Extremely good (5)
L&D (Learning & Development)	O	O	O	O	O
Simple Automation	O	O	O	O	O
Simple automation-based L&D	O	O	O	O	O
Artificial Intelligence	O	O	O	O	O
AI-guided L&D	O	O	O	O	O

Q: How would you rate your level of experience with the following L&D (Learning & Development) programs?

L&D program	No experience (1)	Limited experience (2)	Moderate experience (3)	Experience (4)	Very experienced (5)
Traditional human-led L&D	O	O	O	O	O
Simple automation-based L&D	O	O	O	O	O
AI-guided L&D	O	O	O	O	O

Demographic Questions

In this last section, please answer a few demographic questions. I emphasize that all answers are anonymous and confidential, which implies that I am unable to link your responses to your person.

Q: What is your age?

____

Q: Please specify your gender:
o Male
o Female
o Other (Please specify) ____

Q: Please specify your nationality:
▼ Afghanistan ... Zimbabwe

Q: What is the highest level of education you have completed or the highest degree you have obtained?
o Less than high school degree
o High school graduate
o Some college but no degree
o Associate degree in college
o Bachelor's degree in college
o Master's degree
o Doctoral degree
o Professional degree
o Other (Please specify)_________________________________

Q: What is your current employment status?
o Employed
o Freelancer
o Unemployed
o Student
o Worker and Student
o Retired
o Other (Please specify)_________________________________

Q: How comfortable are you with the English language?
o Extremely uncomfortable (1)
o Somewhat uncomfortable (2)
o Neither comfortable nor uncomfortable (3)
o Somewhat comfortable (4)
o Extremely comfortable (5)

Q: How much attention did you pay during this survey?
o None at all (1)
o A little (2)
o A moderate amount (3)
o A lot (4)
o A great deal (5)

Q: Through which channel or platform did you access this survey?
o E-Mail
o LinkedIn
o Social Media (Instagram, Facebook)
o WhatsApp
o Prolific
o Other (Please specify) ________________________________

Q: Do you have any comments you would like to share with the researcher?
If so, please write them in the box below. Otherwise, just leave it blank.
____

End of Survey text

Thank you for participating in this survey! Your responses have been transmitted.

The goal of this study was to measure how knowing the source of guidance in employee learning and development impacts motivation. Therefore, participants were randomly assigned to an AI guided L&D setting or a simple automation-based/ technology-enhanced L&D setting and then asked questions about their motivation to learn through it.

If you have any questions or comments, do not hesitate to send me an email via s-treitgruber@ucp.pt. Thank you very much again and have a great day!

Appendix 2: Demographic profile of participants

Table A Demographic profile of participants

Demographic characteristic		Sample (N = 144)	Percentage (%)
Gender	**Female**	76	53.00
	Male	68	47.00
Age	**< 18**	2	1.39
	19-29	84	58.33
	30–44	34	23.61
	45–60	23	15.97
	n/a	1	0.69
Highest level of education	**Associate degree in college**	8	5.60
	Bachelor's degree	54	38.00
	Doctoral degree	4	2.80
	High school degree	20	2.80
	Less than high school degree	3	2.10
	Master's degree	41	28.00
	Other	4	2.80
	Professional degree	4	2.80
	Some college but no degree	6	4.20
Employment Status	**Employed**	78	54.00
	Employee and Student	28	19.00
	Freelancer	5	3.50
	Other	2	1.40
	Retired	1	0.70
	Student	28	19.00
	Unemployed	2	1.40
Channel	**E-Mail**	4	2.80
	LinkedIn	6	4.20
	Other	14	9.70
	Prolific	1	0.70
	Social Media (Instagram, Facebook)	29	20.00
	WhatsApp	90	62.00
Condition	**AI-guided L&D**	72	50.00
	Simple automation-based L&D	72	50.00
Nationality	**Australia**	1	0.70
	Austria	87	62.00
	Canada	1	0.70
	Ecuador	1	0.70
	El Salvador	1	0.70
	Germany	20	14.00
	Hungary	1	0.70
	Ireland	1	0.70
	Italy	2	1.40
	Kazakhstan	1	0.70
	Mexico	1	0.70

	Philippines	2	1.40
	Portugal	4	2.90
	Romania	1	0.70
	Serbia	1	0.70
	Ukraine	1	0.70
	United Kingdom of Great Britain and Northern Ireland	2	1.40
	United States of America	10	7.10
	Venezuela, Bolivarian Republic of...	2	1.40
	Unknown	4	2.80
Understanding of L&D	**Bad**	9	6.20
	Neither good nor bad	38	26.00
	Good	80	56.00
	Extremely good	17	12.00
Understanding of simple automation	**Extremely bad**	1	0.70
	Bad	10	6.90
	Neither good nor bad	30	21.00
	Good	79	55.00
	Extremely good	24	17.00
Understanding of simple automation-based L&D	**Extremely bad**	3	2.10
	Bad	19	13.00
	Neither good nor bad	49	34.00
	Good	60	42.00
	Extremely good	13	9.00
Understanding of Artificial Intelligence (AI)	**Extremely bad**	6	4.20
	Bad	12	8.30
	Neither good nor bad	35	24.00
	Good	64	44.00
	Extremely good	27	19.00
Understanding of AI-guided L&D	**Extremely bad**	7	4.90
	Bad	28	19.00
	Neither good nor bad	52	36.00
	Good	43	30.00
	Extremely good	14	9.70
Experience with traditional human-led L&D	**No experience**	13	9.00
	Limited experience	28	19.00
	Moderate experience	38	26.00
	Experienced	45	31.00
	Very experienced	20	14.00
Experience with simple automation-based L&D	**No experience**	27	19.00
	Limited experience	38	26.00
	Moderate experience	43	30.00
	Experienced	30	21.00
	Very experienced	6	4.20
Experience with AI-guided L&D	**No experience**	87	60.00
	Limited experience	33	23.00
	Moderate experience	12	8.30

	Experienced	11	7.60
	Very experienced	1	0.70

Table B Preference of AI-guided and automation-based L&D over usual human-led L&D

Demographic characteristic		**Sample (*N* = 72)**	**Percentage (%)**
Preference of AI-guided L&D over human-led L&D	**Not at all true**	8	11.00
	Slightly untrue	10	14.00
	Neither untrue nor true	22	31.00
	Slightly true	17	24.00
	Very true	15	21.00
Preference of simple automation-based L&D over human-led L&D	**Not at all true**	10	14.00
	Slightly untrue	15	21.00
	Neither untrue nor true	17	24.00
	Slightly true	19	26.00
	Very true	11	15.00

Table C Further descriptives of participants; overall (*N* = 144); and per scenario (*N* = 72)

Question Item	***N* = 144**		***N* = 72**		***N* = 72**	
	M	***SD***	***M* AI ***	***SD* AI***	***M* Auto****	***SD* Auto****
Level of Difficulty	4.26	1.49	4.32	1.45	4.19	1.52
Imagining Scenario	4.54	1.60	4.76	1.54	4.32	1.63
Understanding of L&D	3.73	0.75	3.76	0.75	3.69	0.74
Understanding of automation	3.80	0.82	3.88	0.83	3.72	0.80
Understanding of simple automation-based L&D	3.42	0.90	3.46	0.88	3.39	0.92
Understanding of AI	3.65	1.01	3.60	1.01	3.71	1.01
Understanding of AI-guided L&D	3.20	1.02	3.11	1.01	3.29	1.02
Experience with human-led L&D	3.22	1.18	3.36	1.18	3.07	1.17
Experience with simple automation-based L&D	2.65	1.13	2.53	1.11	2.78	1.14
Experience with AI-guided L&D	1.65	0.97	1.58	0.93	1.72	1.01
Age	31.90	10.86	31.83	10.40	31.96	11.39
Gender	0.53	0.50	0.50	0.50	0.56	0.50
Preference over human-led L&D	3.19	1.27	3.29	1.25	3.08	1.28

*Note: *AI = Sample of AI-guided L&D scenario only; **Auto = Sample of simple automation-based L&D scenario only*
M = Mean; SD = Standard Deviation

Appendix 3: Chi-Square test for Manipulation-Check

Observed Frequencies

Actual Scenario	**Perceived Scenario**		
	AI-guided L&D	Simple automation-based L&D	Total
AI-guided L&D	65	7	72
Simple automation-based L&D	19	53	72
Total	84	60	144

Expected Frequencies (Variables Perfectly Independent)

Actual Scenario	**Perceived Scenario**		
	AI-guided L&D	Simple automation-based L&D	Total
AI-guided L&D	42	30	72
Simple automation-based L&D	42	30	72
Total	84	60	144

Chi-Square Points=(Observed-Expected)^2/Expected

Actual Scenario	**Perceived Scenario**	
	AI-guided L&D	Simple automation-based L&D
AI-guided L&D	12,5952381	17,63333333
Simple automation-based L&D	12,5952381	17,63333333

X^2 (Chi-square):	60,45714286
***df* (degress of freedom):**	1
Chi-Test (*p*)-value:	7,5198E-15

Null hypothesis (H0):	There is no association between the actual scenario and the perceived scenario.	$p > .05$	is rejected
Alternative hypothesis (H1):	There is an association between the actual scenario and the perceived scenario.	$p < .05$	

Appendix 4: Modification Process to improve construct reliability and validity

Table D Initial factor cross-loadings analysis of constructs

	A	BI	C	EE	MTL	PE	R	Scenario	SI
A1	**0.748**	0.368	0.390	0.392	0.436	0.399	0.235	-0.048	0.393
A2	**0.837**	0.498	0.678	0.262	0.639	0.582	0.331	0.115	0.508
A3	**0.819**	0.437	0.608	0.273	0.603	0.500	0.309	0.134	0.337
A4	**0.729**	0.312	0.360	0.336	0.459	0.410	0.276	0.065	0.335
BI1	0.471	**0.925**	0.518	0.361	0.684	0.633	0.394	0.006	0.715
BI2	0.476	**0.910**	0.509	0.359	0.664	0.652	0.304	-0.027	0.638
BI3	0.345	**0.605**	0.414	0.260	0.419	0.438	0.207	0.082	0.265
C1	0.572	0.468	**0.840**	0.251	0.618	0.586	0.339	0.136	0.501
C2	0.547	0.526	**0.871**	0.226	0.667	0.662	0.317	0.240	0.377
C3	0.543	0.430	**0.766**	0.362	0.529	0.480	0.258	0.013	0.370
C4	0.269	0.211	**0.335**	0.374	0.227	0.186	0.256	-0.041	0.092
EE1	0.474	0.371	0.441	**0.747**	0.443	0.444	0.307	0.080	0.401
EE2	0.124	0.298	0.120	**0.813**	0.111	0.171	0.240	-0.221	0.144
EE3	0.330	0.272	0.307	**0.823**	0.265	0.230	0.185	-0.104	0.208
MTL1	0.692	0.709	0.660	0.351	**0.899**	0.634	0.419	0.065	0.604
MTL2	0.584	0.619	0.682	0.314	**0.888**	0.665	0.474	0.196	0.510
MTL3	0.598	0.637	0.640	0.261	**0.917**	0.674	0.438	0.175	0.526
PE1	0.594	0.690	0.680	0.408	0.673	**0.852**	0.367	0.129	0.575
PE2	0.484	0.463	0.483	0.389	0.537	**0.778**	0.247	0.000	0.440
PE3	0.522	0.595	0.629	0.236	0.591	**0.884**	0.193	0.055	0.546
PE4	0.418	0.545	0.485	0.156	0.599	**0.798**	0.322	0.194	0.363
R1	0.318	0.343	0.270	0.326	0.359	0.365	**0.736**	-0.043	0.266
R2	0.281	0.300	0.323	0.283	0.415	0.236	**0.876**	-0.121	0.257
R3	0.318	0.286	0.357	0.169	0.430	0.262	**0.839**	0.076	0.281
SI1	0.434	0.588	0.463	0.261	0.565	0.494	0.283	0.000	**0.880**
SI2	0.516	0.637	0.464	0.309	0.561	0.530	0.241	-0.087	**0.902**
SI3	0.356	0.573	0.351	0.257	0.456	0.506	0.332	-0.088	**0.822**
Scenario	0.098	0.012	0.157	-0.102	0.159	0.121	-0.035	**1.000**	-0.068

Note: A= Autonomy; BI = Behavioural Intention to Use; C = Competence, EE = Effort Expectancy; MTL = Motivation to learn; PE = Performance Expectancy; R = Relatedness; Scenario = Mode of L&D delivery scenario; SI = Social Influence

Table E Initial Construct reliability overview

Construct	α	ρ_a	ρ_c	AVE
Autonomy	0.795	0.816	0.865	0.616
Behavioural Intention to Use	0.759	0.840	0.862	0.683
Competence	**0.695**	0.796	0.812	0.541
Effort Expectancy	0.709	0.708	0.837	0.632
Motivation to learn	0.884	0.886	0.928	0.812
Performance Expectancy	0.849	0.866	0.898	0.688
Relatedness	0.752	0.762	0.859	0.671
Social Influence	0.836	0.840	0.902	0.754

Note: α = Cronbach's alpha; ρ_a= Reliability; ρ_c= Composite reliability; AVE = Average variance extracted

Appendix 5: Measurement model for reflective constructs and model fit

Table F Factor cross-loadings analysis of constructs **after modification**

	A	BI	C	EE	MTL	PE	R	Scenario	SI
A1	**0.748**	0.347	0.368	0.397	0.436	0.399	0.235	-0.048	0.393
A2	**0.837**	0.478	0.683	0.270	0.639	0.582	0.331	0.115	0.506
A3	**0.819**	0.412	0.604	0.279	0.602	0.499	0.309	0.134	0.336
A4	**0.729**	0.308	0.335	0.339	0.459	0.410	0.276	0.065	0.335
BI1	0.471	**0.947**	0.504	0.366	0.684	0.632	0.394	0.006	0.715
BI2	0.476	**0.942**	0.515	0.363	0.664	0.652	0.304	-0.027	0.638
C1	0.572	0.444	**0.850**	0.259	0.618	0.586	0.339	0.136	0.501
C2	0.547	0.500	**0.890**	0.235	0.667	0.662	0.317	0.240	0.377
C3	0.543	0.397	**0.754**	0.367	0.529	0.481	0.258	0.013	0.369
EE1	0.474	0.379	0.448	**0.767**	0.443	0.444	0.307	0.080	0.401
EE2	0.124	0.276	0.078	**0.802**	0.111	0.171	0.240	-0.221	0.144
EE3	0.330	0.244	0.248	**0.811**	0.265	0.229	0.185	-0.104	0.207
MTL1	0.692	0.699	0.650	0.356	**0.898**	0.633	0.419	0.065	0.603
MTL2	0.584	0.610	0.681	0.321	**0.888**	0.665	0.474	0.196	0.509
MTL3	0.598	0.618	0.642	0.270	**0.917**	0.673	0.438	0.175	0.526
PE1	0.594	0.659	0.672	0.415	0.673	**0.850**	0.367	0.129	0.575
PE2	0.484	0.450	0.470	0.392	0.537	**0.779**	0.247	0.000	0.440
PE3	0.522	0.587	0.643	0.244	0.591	**0.886**	0.193	0.055	0.546
PE4	0.418	0.522	0.495	0.164	0.599	**0.797**	0.322	0.194	0.364
R1	0.318	0.349	0.251	0.327	0.359	0.365	**0.736**	-0.043	0.267
R2	0.281	0.291	0.303	0.285	0.415	0.235	**0.875**	-0.121	0.258
R3	0.318	0.279	0.344	0.175	0.430	0.261	**0.839**	0.076	0.282
SI1	0.434	0.605	0.466	0.270	0.565	0.494	0.283	0.000	**0.878**
SI2	0.516	0.652	0.463	0.313	0.561	0.530	0.241	-0.087	**0.900**
SI3	0.356	0.609	0.364	0.264	0.456	0.506	0.332	-0.088	**0.826**
Scenario	0.098	-0.011	0.168	-0.095	0.159	0.120	-0.035	**1.000**	-0.068

Note: A= Autonomy; BI = Behavioural Intention to Use; C = Competence, EE = Effort Expectancy; MTL = Motivation to learn; PE = Performance Expectancy; R = Relatedness; Scenario = Mode of L&D delivery scenario; SI = Social Influence

Table G Descriptive statistics and construct reliability and validity **after modification**

Construct	Indicator	M	SD	α	ρ_a	ρ_c	AVE	VIF
Autonomy	A1	3.01	1.31	0.795	0.816	0.865	0.616	1.738
	A2	3.06	1.15					1.788
	A3	2.82	1.25					1.757
	A4	3.12	1.28					1.654
Behavioural Intention to Use	BI1	3.71	1.20	0.879	0.880	0.943	0.892	2.589
	BI2	3.36	1.19					2.589
Competence	C1	3.42	1.07	0.779	0.800	0.871	0.694	1.772
	C2	3.51	1.10					1.945
	C3	3.49	1.10					1.419
Effort Expectancy	EE1	3.49	1.12	0.709	0.709	0.836	0.630	1.232
	EE2	3.65	1.07					1.554
	EE3	3.90	0.94					1.679
Motivation to	MTL1	3.17	1.18	0.884	0.886	0.928	0.812	2.423

learn	MTL2	3.55	1.17					2.371
	MTL3	3.23	1.15					2.954
Performance Expectancy	PE1	3.62	1.08	0.849	0.865	0.898	0.688	1.916
	PE2	3.71	1.06					1.798
	PE3	3.59	1.15					2.544
	PE4	3.55	1.11					1.772
Relatedness	R1	3.27	1.13	0.752	0.762	0.859	0.671	1.324
	R2	3.64	1.03					1.900
	R3	3.37	1.01					1.705
Social Influence	SI1	3.90	1.05	0.836	0.839	0.902	0.754	2.273
	SI2	3.86	1.12					2.411
	SI3	3.92	1.04					1.638
Scenario		0.50	0.50					1.000

Note: M= Mean; SD = Standard Deviation; α = Cronbach's Alpha (.70 - .90); ρ_a =Reliability (> .70); ρ_c = Composite reliability (> .70) ; AVE = Average Variance Extracted (> .50) ; VIF = Collinearity statistics outer model (< 3.3)

Table H Descriptive statistics, Cronbach's alpha (CA), Composite Reliability (CR), Average Variance Extracted (AVE) per Construct **after modification**

Construct	M	SD	CA	CR	AVE	A	BI	CI	EE	MTL	PE	R	SC	SI
A	3.00	0.985	0.795	0.865	0.616	**0.785**								
BI	3.53	1.135	0.879	0.943	0.892	0.501	**0.944**							
C	3.47	0.911	0.779	0.871	0.694	0.661	0.540	**0.833**						
EE	3.68	0.830	0.709	0.836	0.630	0.395	0.386	0.334	**0.794**					
MTL	3.32	1.057	0.884	0.928	0.812	0.695	0.714	0.730	0.352	**0.901**				
PE	3.62	0.916	0.849	0.898	0.688	0.613	0.679	0.698	0.366	0.729	**0.829**			
R	3.43	0.863	0.752	0.859	0.671	0.372	0.370	0.368	0.316	0.492	0.345	**0.819**		
SC						0.098	-0.011	0.168	-0.095	0.159	0.120	-0.035	**1.000**	
SI	3.89	0.933	0.836	0.902	0.754	0.504	0.717	0.497	0.326	0.608	0.588	0.328	-0.068	**0.868**

*Note: **AVE square root in bold***
A= Autonomy; BI = Behavioural Intention to Use; C = Competence, EE = Effort Expectancy; MTL = Motivation to learn; PE = Performance Expectancy; R = Relatedness; Scenario = Mode of L&D delivery scenario; SI = Social Influence; M = Mean; SD = Standard Deviation

Discriminant validity:

Table I Heterotrait-monotrait ratio (HTMT) analysis of constructs **after modification**

Construct	A	BI	CI	EE	MTL	PE	R	Scenario	SI
A									
BI	0.587								
C	0.810	0.649							
EE	0.537	0.477	0.452						
MTL	0.807	0.808	0.875	0.432					
PE	0.726	0.774	0.837	0.457	0.835				
R	0.476	0.460	0.477	0.429	0.603	0.434			
Scenario	0.129	0.019	0.176	0.202	0.171	0.123	0.113		
SI	0.610	0.835	0.618	0.409	0.704	0.688	0.416	0.073	

Note: A = Autonomy; BI = Behavioural Intention to Use; C = Competence, EE = Effort Expectancy; MTL = Motivation to learn; PE = Performance Expectancy; R = Relatedness; Scenario = Mode of L&D delivery scenario; SI = Social Influence

Table J Fornell-Larcker criterion **after modification**

Construct	A	BI	CI	EE	MTL	PE	R	Scenario	SI
A	0.785								
BI	0.501	0.944							
C	0.661	0.540	0.833						
EE	0.395	0.386	0.334	0.794					
MTL	0.695	0.714	0.730	0.352	0.901				
PE	0.613	0.679	0.698	0.366	0.729	0.829			
R	0.372	0.370	0.368	0.316	0.492	0.345	0.819		
Scenario	0.098	-0.011	0.168	-0.095	0.159	0.120	-0.035	1.000	
SI	0.504	0.717	0.497	0.326	0.608	0.588	0.328	-0.068	0.868

Note: A = Autonomy; BI = Behavioural Intention to Use; C = Competence, EE = Effort Expectancy; MTL = Motivation to learn; PE = Performance Expectancy; R = Relatedness; Scenario = Mode of L&D delivery scenario; SI = Social Influence

Table K Model fit

Model fit measures	Saturated model	Estimated model
SRMR	0.085	0.299
d_ULS	2.513	31.395
d_G	0.894	1.702
χ^2	737.692	1169.334
NFI	0.698	0.522

Note: SRMR = Standardized Root Mean Square Residual; d_ULS = squared Euclidean distance; d_G = geodesic distance; χ^2 *= Chi-square; NFI = Normed Fit Index*

Appendix 6: Assessment of the structural model

Table L Collinearity statistics (VIF) – Inner model - Matrix

Construct	A	BI	C	EE	MTL	PE	R	SC	SI
A					1.840				
BI									
C					1.879				
EE		1.216							
MTL		2.488							
PE		2.356							
R					1.210				
SC	1.000	1.102	1.000	1.000	1.041	1.000	1.000		1.000
SI		1.804							

Note: A= Autonomy; BI = Behavioural Intention to Use; C = Competence, EE = Effort Expectancy; MTL = Motivation to learn; PE = Performance Expectancy; R = Relatedness; Scenario = Mode of L&D delivery scenario; SI = Social Influence

Table M R-square – Overview

Construct	R^2	R^2 adjusted
Autonomy	0.010	0.003
Behavioural Intention to Use	0.665	0.653
Competence	0.028	0.021
Effort Expectancy	0.009	0.002
Motivation to learn	0.653	0.643
Performance Expectancy	0.014	0.007
Relatedness	0.001	-0.006
Social Influence	0.005	-0.002

Note: R^2 = R-square; R^2adjusted = R-square adjusted

Table N F-square Matrix

Construct	A	BI	C	EE	MTL	PE	R	SC	SI
A					0.170				
BI									
C					0.272				
EE		0.012							
MTL		0.122							
PE		0.055							
R					0.112				
SC	0.010	0.008	0.029	0.009	0.011	0.015	0.001		0.005
SI		0.233							

Note: A= Autonomy; BI = Behavioural Intention to Use; C = Competence, EE = Effort Expectancy; MTL = Motivation to learn; PE = Performance Expectancy; R = Relatedness; Scenario = Mode of L&D delivery scenario; SI = Social Influence

Table O PLSpredict MV prediction summary – Overview

Indicator	Q²predict	PLS-SEM RMSE	PLS-SEM MAE	LM RMSE	LM MAE
A1	-0.053	1.362	1.219	1.336	1.180
A2	-0.010	1.165	1.001	1.160	0.990
A3	-0.002	1.255	1.098	1.251	1.094
A4	-0.020	1.302	1.138	1.298	1.125
BI1	-0.022	1.215	0.912	1.208	0.908
BI2	-0.023	1.205	0.999	1.199	0.995
C1	-0.034	1.097	0.872	1.079	0.894
C2	0.024	1.095	0.848	1.085	0.860
C3	-0.081	1.153	0.949	1.118	0.947
EE1	-0.072	1.171	0.964	1.139	0.948
EE2	0.015	1.069	0.878	1.059	0.863
EE3	-0.021	0.955	0.761	0.947	0.743
MTL1	-0.070	1.229	1.008	1.195	0.973
MTL2	0.010	1.174	0.934	1.165	0.950
MTL3	-0.005	1.164	0.933	1.150	0.913
PE1	-0.014	1.095	0.830	1.087	0.834
PE2	-0.055	1.096	0.846	1.075	0.843
PE3	-0.049	1.184	0.955	1.164	0.964
PE4	0.016	1.110	0.882	1.106	0.881
R1	-0.015	1.143	0.917	1.142	0.916
R2	-0.012	1.044	0.850	1.036	0.837
R3	-0.037	1.031	0.840	1.019	0.826
SI1	-0.040	1.077	0.808	1.065	0.793
SI2	-0.018	1.141	0.843	1.135	0.834
SI3	-0.012	1.048	0.763	1.044	0.752

Note: PLS-SEM RMSE = PLS-SEM root mean squared error; PLS-SEM MAE = PLS-SEM mean absolute error; LM RMSE = Linear regression model root mean squared error; LM MAE = Linear regression model absolute error

A= Autonomy; BI = Behavioural Intention to Use; C = Competence, EE = Effort Expectancy; MTL = Motivation to learn; PE = Performance Expectancy; R = Relatedness; Scenario = Mode of L&D delivery scenario; SI = Social Influence

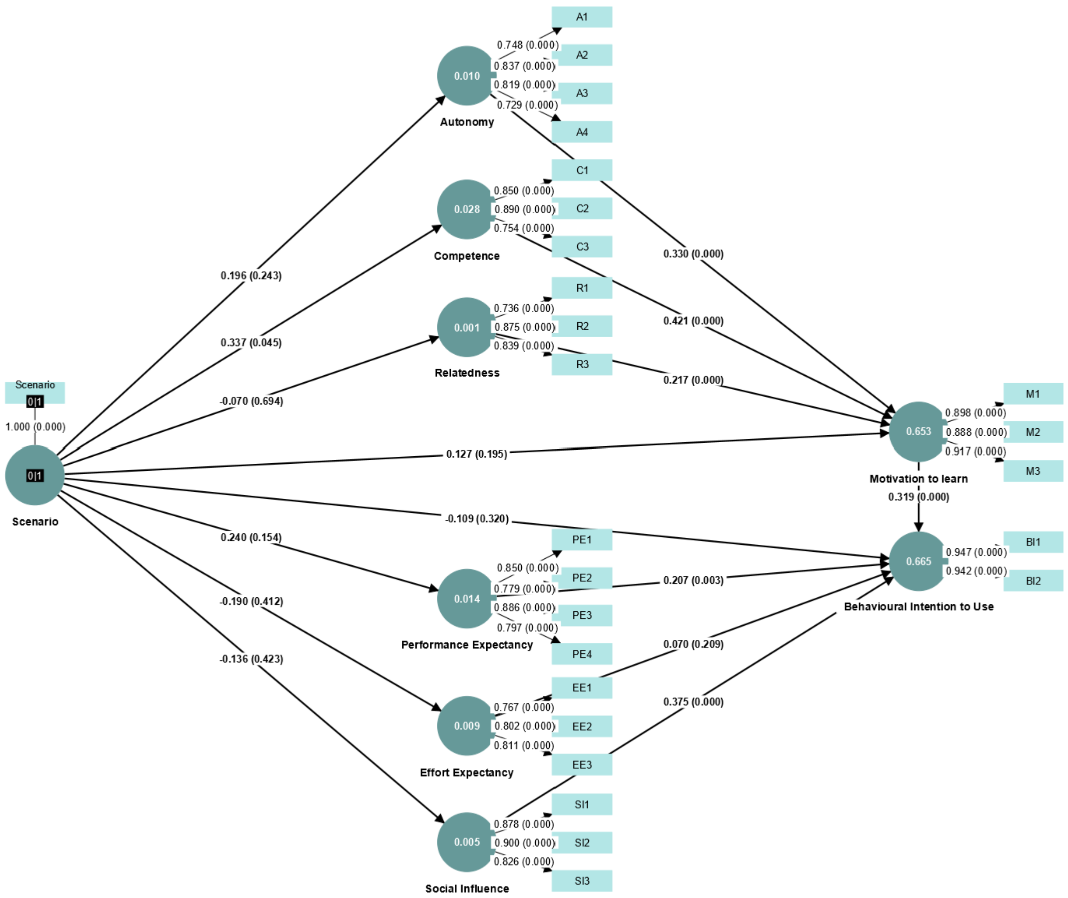
Table P Latent Variables prediction summary – PLS-SEM

Construct	Q²predict	RMSE	MAE
Autonomy	-0.030	1.028	0.863
Behavioural Intention to Use	-0.025	1.031	0.785
Competence	-0.040	1.036	0.829
Effort Expectancy	-0.045	1.034	0.813
Motivation to learn	-0.027	1.028	0.816
Performance Expectancy	-0.034	1.036	0.800
Relatedness	-0.032	1.031	0.823
Social Influence	-0.030	1.037	0.750

Note: RMSE = root mean squared error; MAE = mean absolute error

Appendix 7: Hypothesis testing

Figure A Path estimates of the proposed structural model detailed



*Note: *p-values are displayed in the brackets after the respective path coefficients (= Beta-Coefficients)*

Table Q Path coefficients of PLS-SEM (Direct effects)

Direct effect	ß	*M*	*SD*	*t*	*p*
Autonomy -> Motivation to learn	0.330	0.327	0.074	4.459	0.000
Competence -> Motivation to learn	0.421	0.424	0.076	5.553	0.000
Effort Expectancy -> Behavioural Intention	0.070	0.071	0.056	1.256	0.209
Motivation to learn -> Behavioural Intention	0.319	0.315	0.076	4.217	0.000
Performance Expectancy -> Behavioural Intention	0.207	0.212	0.070	2.972	0.003
Relatedness -> Motivation to learn	0.217	0.218	0.061	3.528	0.000
Scenario -> Autonomy	0.196	0.195	0.168	1.168	0.243
Scenario -> Behavioural Intention	-0.109	-0.106	0.109	0.994	0.320
Scenario -> Competence	0.337	0.340	0.168	2.002	0.045
Scenario -> Effort Expectancy	-0.190	-0.184	0.231	0.820	0.412
Scenario -> Motivation to learn	0.127	0.128	0.098	1.295	0.195
Scenario -> Performance Expectancy	0.240	0.239	0.168	1.426	0.154
Scenario -> Relatedness	-0.070	-0.071	0.178	0.393	0.694
Scenario -> Social Influence	-0.136	-0.141	0.170	0.800	0.423
Social Influence -> Behavioural Intention	0.375	0.373	0.078	4.779	0.000

Note: ß = Beta-Coefficient; M = Sample mean; SD = Standard Deviation; t = t-value; p = p-value;
Behavioural Intention = Behavioural Intention to use; Scenario = Mode of L&D delivery scenario

Table R Total effects between specific variables

Total effect	ß	*M*	Bias	2.5%	97.5%	*SD*	*t*	*p*
Scenario -> Behavioural intention to use	-0.068	-0.029	0.039	-0.382	0.349	0.208	0.325	0.745
Scenario -> Motivation to learn	0.368	0.394	0.026	-0.412	0.601	0.175	2.104	0.035

Note: ß = Beta-Coefficient; M = Sample mean; SD = Standard Deviation; t = t-value; p = p-value; Scenario = Mode of L&D delivery scenario

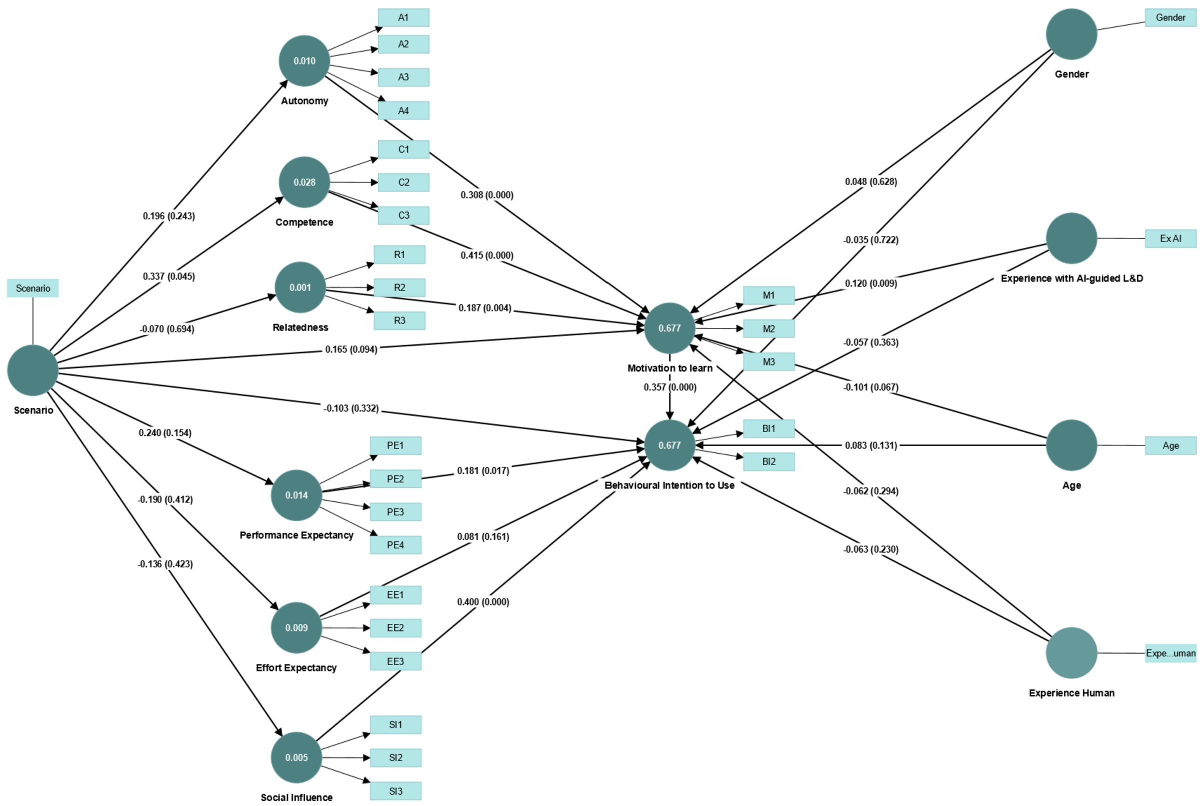
Table S Support of structural model assessment hypothesis

Hypothesis	Supported
H1: AI-guided L&D leads to a higher perception of autonomy, which in turn leads to higher motivation to learn compared to simple automation-based L&D	*Not supported*
H2: AI-guided L&D leads to a higher perception of competence, which in turn leads to higher motivation to learn compared to simple automation-based L&D.	*Supported*
H3: AI-guided L&D leads to a higher perception of relatedness, which in turn leads to higher motivation to learn compared to simple automation-based L&D	*Not supported*
H4: The mode of L&D delivery impacts motivation to learn, such that AI-guided L&D leads to higher motivation to learn than simple automation-based L&D.	*Supported*
H5: The mode of L&D delivery impacts the behavioural intention to use the L&D program such that AI-guided L&D leads to a higher behavioural intention to use compared to simple automation-based L&D.	*Not supported*
H6: AI-guided L&D leads to higher performance expectancy, which in turn leads to a higher behavioural intention to use compared to simple automation-based L&D.	*Not supported*
H7: AI-guided L&D leads to lower effort expectancy, which in turn leads to a higher behavioural intention to use compared to simple automation-based L&D.	*Not supported*
H8: AI-guided L&D leads to higher social influence, which in turn leads to a higher behavioural intention to use compared to simple automation-based L&D.	*Not supported*
H9: Motivation to learn impacts the behavioural intention to use the L&D program.	*Supported*
H10: AI-guided L&D leads to higher motivation to learn which then leads to a higher intention to use compared to simple automation-based L&D.	*Supported**

*Note: * marginal significance*

Appendix 8: Exploratory Analyses

Figure B Structural Model including control variables with path coefficients and p-values



*Note: *p-values are displayed in the brackets after the respective path coefficients (= Beta-Coefficients)*

Table T Path coefficients including control variables (Direct Effects)

Direct effects	**ß**	***M***	***SD***	***t***	***p***
Age -> Behavioural Intention to use	0.083	0.082	0.055	1.511	0.131
Age -> Motivation to learn	-0.101	-0.102	0.055	1.835	0.067
Autonomy -> Motivation to learn	0.308	0.306	0.069	4.464	0.000
Competence -> Motivation to learn	0.415	0.418	0.074	5.577	0.000
Effort Expectancy -> Behavioural Intention to use	0.081	0.080	0.058	1.401	0.161
Experience Human L&D -> Bevioural Intention to use	-0.063	-0.061	0.053	1.200	0.230
Experience Human L&D -> Motivation to learn	-0.062	-0.062	0.059	1.050	0.294
Experience AI L&D -> Behavioural Intention to use	-0.057	-0.056	0.062	0.910	0.363
Experience AI L&D -> Motivation to learn	0.120	0.121	0.046	2.615	0.009
Gender -> Behavioural Intention to use	-0.035	-0.041	0.099	0.355	0.722
Gender -> Motivation to learn	0.048	0.046	0.100	0.484	0.628
Motivation to learn -> Behavioural Intention to use	0.357	0.352	0.076	4.713	0.000
Performance Expectancy -> Behavioural Intention to use	0.181	0.187	0.076	2.380	0.017
Relatedness -> Motivation to learn	0.187	0.187	0.064	2.911	0.004
Scenario -> Autonomy	0.196	0.195	0.168	1.168	0.243
Scenario -> Behavioural Intention to use	-0.103	-0.103	0.106	0.969	0.332
Scenario -> Competence	0.337	0.340	0.168	2.002	0.045

Scenario -> Effort Expectancy	-0.190	-0.184	0.231	0.821	0.412
Scenario -> Motivation to learn	0.165	0.167	0.099	1.675	0.094
Scenario -> Performance Expectancy	0.240	0.239	0.168	1.425	0.154
Scenario -> Relatedness	-0.070	-0.071	0.178	0.393	0.694
Scenario -> Social Influence	-0.136	-0.141	0.170	0.800	0.423
Social Influence -> Behavioural Intention to use	0.400	0.397	0.082	4.868	0.000

Note: ß = Beta-Coefficient; SD = Standard Deviation; t = t-value; p = p-value; Scenario = Mode of L&D delivery scenario

Table U Specific indirect effects - Confidence intervals bias corrected incl. control variables

Specific indirect effect	**ß**	***M***	**Bias**	**2.5%**	**97.5%**	***SD***	***t***	***p***
Scenario -> R -> MTL	-0.013	-0.015	-0.002	-0.099	0.047	0.036	0.365	0.715
Scenario -> PE -> BI	0.043	0.045	0.002	-0.011	0.147	0.039	1.115	0.265
R -> MTL -> BI	0.067	0.066	-0.001	0.021	0.136	0.029	2.342	0.019
C -> MTL -> BI	0.148	0.147	-0.001	0.077	0.243	0.042	3.565	0.000
A -> MTL -> BI	0.110	0.107	-0.003	0.058	0.185	0.032	3.468	0.001
Scenario -> C -> MTL -> BI	0.050	0.049	-0.001	0.008	0.117	0.026	1.883	0.060
ExAI -> MTL -> BI	0.043	0.042	-0.001	0.013	0.088	0.019	2.297	0.022
Scenario -> EE -> BI	-0.015	-0.018	-0.002	-0.082	0.015	0.024	0.646	0.518
Gender -> MTL -> BI	0.017	0.017	-0.000	-0.047	0.097	0.036	0.475	0.635
Age -> MTL -> BI	-0.036	-0.036	0.000	-0.089	-0.001	0.022	1.649	0.099
ExHuman -> MTL -> BI	-0.022	-0.022	-0.000	-0.071	0.016	0.022	1.017	0.309
Scenario -> C -> MTL	0.140	0.140	0.001	0.005	0.290	0.071	1.955	0.051*
Scenario -> A -> MTL -> BI	0.022	0.021	-0.001	-0.010	0.071	0.020	1.087	0.277
Scenario -> A -> MTL	0.060	0.061	0.000	-0.035	0.188	0.055	1.088	0.277
Scenario -> R-> MTL -> BI	-0.005	-0.006	-0.001	-0.039	0.016	0.013	0.353	0.724
Scenario -> SI -> BI	-0.054	-0.056	-0.002	-0.203	0.076	0.070	0.781	0.435
Scenario -> MTL -> BI	0.059	0.060	0.001	-0.005	0.154	0.040	1.488	0.137

*Note: * marginally significant mediating effect of C in the relationship between SC and MTL*

ß = Beta-Coefficient; M = Sample Mean; SD = Standard Deviation; t = t-value; p = p-value;
A= Autonomy; BI = Behavioural Intention to use; C = Competence, EE = Effort Expectancy; MTL = Motivation to learn; PE = Performance Expectancy; R = Relatedness; Scenario = Mode of L&D delivery scenario; SI = Social Influence; ExAI = Experience with AI-guided L&D; ExHuman = Experience with human-led L&D