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Technology-mediated learning in the workplace: influence of personalization

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Abstract

Purpose – Technology-mediated learning (TML) is gaining popularity among business organizations for upskilling their employees. However, high dropout rates have limited its effectiveness. Thus, we explore, if and how personalization of TML can improve its adoption and effectiveness in workplaces from the lens of the unified theory of acceptance and use of technology (UTAUT2) theory.

Design/methodology/approach – An exploratory sequential mixed-method design was used for this study. Study 1 included interviews ($N = 27$) of Learning and Development (L&D) leaders and employees (learners) of large global organizations, about their experiences with TML. Emergent themes led us to our research model, which integrates constructs of personalization, technology adoption and transfer of training (TT). In Study 2, a cross-sectional study was conducted. Data were collected from employees who have experienced TML ($N = 406$) and analyzed using PLS-SEM.

Findings – Findings suggested that personalization of TML positively influenced intent to use TML and transfer skills, thereby improving TML effectiveness and proving its relevance in workplaces. Precisely, personalized TML recommendations from managers impacted (1) behavioral intention (BI) and TT directly; (2) BI through performance expectancy (PE); (3) TT through social influence and BI individually; and (4) TT through PE and BI sequentially. Likewise, allowing employees the flexibility to choose TML based on their interests influenced (1) BI directly and via hedonic motivation (HM) and (2) TT via HM and BI individually and sequentially.

Practical implications – Using our model, L&D practitioners may design and personalize their TML ecosystems to foster adoption and transfer of training in workplaces.

Originality/value – Personalization of learning in workplaces has received scant attention; thereby, our study expands existing knowledge in this relatively nascent field of research.

Keywords Technology-mediated learning, Personalization of learning, Technology adoption, Transfer of training

Paper type Research paper

1. Introduction

Technology-mediated learning (TML) has become quite popular among business organizations since the COVID-19 pandemic, when businesses were forced to adopt a remote or hybrid work culture (Moglia *et al.*, 2021; Bhat *et al.*, 2022). TML offers many benefits to the organizations and their employees (learners), such as allowing organizations to gain cost efficiency and support the upskilling needs of geographically dispersed employees while offering a greater degree of flexibility to employees to learn at their own pace and time (Panigrahi *et al.*, 2018). However, the adoption of TML amongst employees has been a concern, and studies have reported high attrition rates (75%–90%), i.e. learners discontinue the use of TML (Fake and Dabbagh, 2020; Huber *et al.*, 2023). Such high levels of attrition, or low levels of adoption and continued use, have raised questions about the effectiveness of TML, especially at a time when businesses are planning to increase their investment in TML

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(Gartner, 2022; Liu and Yu, 2023). High attrition rates are a cause of concern, as they not only impact utilization but also performance (Sitzmann and Weinhardt, 2019). Given the importance of TML in the current and future workplace context, our study seeks to find ways to improve its adoption, continued use and effectiveness.

Previous studies have cited multiple reasons that may have prompted learners to drop out of TML, including lack of time, flawed design, lack of perceived usefulness and lack of engagement and motivation (Zhou, 2017; Sitzmann and Weinhardt, 2019; Huber *et al.*, 2023). While utilization of training resources is one of the measures to gauge effectiveness, there are other indicators to be considered, such as affective indicators, performance indicators and impact on business (Sitzmann and Weinhardt, 2019). One of the key performance indicators is the transfer of training, i.e. the extent to which learners apply their knowledge and skills in real-world situations. Transfer of training has a direct impact on performance and business results; thus, it has received a lot of attention (Ford *et al.*, 2018). Baldwin and Ford (1988) proposed a framework explaining the transfer of training, which has since been used in multiple studies. In their framework, various constructs, including motivation and support from peers and leaders, predict the transfer of training (Rahman and Bockarie, 2021; Sitzmann and Weinhardt, 2019; Greenan, 2023).

To improve TML's effectiveness, there's a need to reduce the attrition rates and increase the transfer of training. Studies have shown that increasing employees' motivation to participate in a program increases the probability of transfer (Nafukho *et al.*, 2023). Increased participation and transfer can be achieved by adopting practices that result in a combination of increased motivation levels, improved perceived usefulness and enhanced supervisory support. Personalization has been reported to positively influence perceived usefulness of learning and motivation levels of learners (Geng *et al.*, 2019; Jeong *et al.*, 2012). Also, studies show that supervisors can play a crucial role in personalizing learning for their team members (Fake and Dabbagh, 2020). So, personalization can possibly achieve the desired combination and improve TML's adoption and effectiveness. Further, researchers have reported that adult learners are self-directed, and personalized platforms can support them to make their learning experiences effective (Ritz *et al.*, 2024). However, personalization of learning in workplaces has received limited attention from researchers (Bernacki *et al.*, 2021; Xie *et al.*, 2019; Fake and Dabbagh, 2023a). In this study, we attempt to delve into this relatively uncharted field of research and explore if and how personalization of learning can improve the effectiveness of TML. Precisely, we address *whether and how (1) personalization of learning can improve adoption and continued use of TML among employees of business organizations and (2) personalized learning influences the transfer of knowledge and skills gained from TML.*

To explore these, we have employed an exploratory sequential mixed-method research design—semi-structured interviews of Learning and Development (L&D) leaders and employees (learners) of large global organizations in Study 1, followed by a cross-sectional study involving employees (learners) in Study 2 (Kumar *et al.*, 2019).

Since not many studies are available in the literature that throw light on enhancing TML adoption and effectiveness in workplaces, this paper has first delved into multiple scholarships, namely, learning effectiveness, personalization of learning, TML and technology adoption (unified theory of acceptance and use of technology (UTAUT2)), followed by the qualitative interviews of the L&D leaders and learners to understand about their TML experiences. These interviews were mainly aimed at understanding the interconnections between the aforementioned scholarships and developing hypotheses based on emergent themes. The proposed model and associated hypotheses were then validated through a cross-sectional study using PLS-SEM.

Our model extends the UTAUT2 to enhance adoption and effectiveness of TML in workplaces. No previous study has integrated constructs of personalization, technology adoption and learning effectiveness to offer solutions for TML-related challenges faced by organizations. The findings from this study contribute some new insights to the scholarship as well as to the practicing professionals. Our model may guide the L&D practitioners to design more effective personalization-based TML systems in workplaces, offering their employees relevant and flexible learning opportunities.

2. Literature review

2.1 Learning effectiveness

Learning effectiveness refers to the degree to which learning goals are met. Measurement of learning effectiveness is critical, as it helps determine if learning initiatives have met their business objectives (Alsalamah and Callinan, 2021). In an organizational set-up, effectiveness of training is measured in terms of how the training resources are being utilized, how employees are reacting to learning experiences, how learning offerings are impacting performance and what's their return on investment (Sitzmann and Weinhardt, 2019; Alsalamah and Callinan, 2021). Training utilization comprises the number of enrolments, percentage completions and attrition rates. High attrition rates not only affect utilization but also negatively impact performance, as individuals who need to gain skills and knowledge are unable to do so if they don't consume the learning (Sitzmann and Weinhardt, 2019). Affective indicators, such as learners' satisfaction and motivation levels, also predict the effectiveness of learning. Researchers have reported motivation is a predictor of utilization, learning and transfer of training (Panigrahi *et al.*, 2018; Ford *et al.*, 2018; Torresan and Hinterhuber, 2023). Performance and return on investment are the other indicators of learning effectiveness. These are gauged by how learning experiences support the development of knowledge and skills, which are then transferred to the job and impact individuals' and businesses' growth (Fawad Latif, 2012; Sitzmann and Weinhardt, 2019).

In business organizations, transfer of training is the most important effectiveness indicator, as it improves on-the-job performance (Blume *et al.*, 2019; Martins *et al.*, 2019; Pilbeam and Karanikas, 2023). Yet, studies have reported fairly low levels of transfer (Bhat *et al.*, 2022), with transfer rates ranging from 10% to 30%, i.e. less than 30% of learned skills are applied by learners in their jobs (Sitzmann and Weinhardt, 2019; Yang *et al.*, 2020). The gap between what is learned and what is transferred is known as the training transfer problem (Pilbeam and Karanikas, 2023). Many organizations have increased their training investments and efforts to address the transfer problem; however, that hasn't translated into improved transfer of skills and knowledge to the workplace (Yang *et al.*, 2020; Bhat *et al.*, 2022).

2.2 Technology-mediated learning (TML)

TML has been defined as learning where technology acts as a mediator between learners and the source of learning, which could be their peers, facilitators and/or learning resources (Hu and Hui, 2012). TML includes various learning approaches, such as online facilitated sessions, self-directed learning and team-based learning (Janson *et al.*, 2020). Organizations are adopting TML, as it helps reduce the overall cost of training and allows them to offer learning opportunities to a geographically dispersed workforce (Dachner *et al.*, 2021; Panigrahi *et al.*, 2018). Furthermore, the COVID pandemic and subsequent adoption of a hybrid working model compelled organizations to induct TML (Mikołajczyk, 2021; Moglia *et al.*, 2021). Organizations are reporting increased investment in TML, including diversification of channels such as virtual learning, eLearning, MOOCs, mobile learning and chatbots. Of the multiple channels, eLearning courses and online videos have been the most popular (Gartner, 2022). Previous studies have reported that TML can be as effective as traditional classroom training sessions (Hu and Hui, 2012; Carter and Youssef-Morgan, 2022); however, TML is plagued by issues such as high attrition rates and cognitive overload (Fake and Dabbagh, 2020; Panigrahi *et al.*, 2018; Liu and Yu, 2023). A common cause of these issues is that many organizations introduce TML without considering fundamentals that support learning, such as multimedia principles, and this negatively impacts cognition and engagement (Çeken and Taşkın, 2022; Sweller, 2019; Gartner, 2022). In addition, increasing investments and diversification of channels have resulted in too many TML resources leading to extraneous cognitive load, as learners' cognitive effort is spent in searching for relevant resources (Geng *et al.*, 2019; Nair *et al.*, 2017; Hemmler *et al.*, 2023). This is detrimental to learning, as it takes away a portion of the limited cognitive capacity without promoting learning (Janson *et al.*, 2020). Further, employees have reported "lack of time" as one of the primary barriers to learning, and losing time to search for relevant resources isn't ideal (Linkedin, 2020). Existing literature suggests lack of perceived usefulness and lack of motivation as some of the other reasons for high attrition rates in TML (Fake and Dabbagh, 2020; Romero-Rodríguez *et al.*, 2020; Zhou, 2017).

Studies have reported that cognitive, affective and motivational elements work together to improve engagement levels and lack of engagement leads to attrition (Huber *et al.*, 2023). Thus, designing a TML ecosystem that reduces cognitive load and increases learner engagement will result in improved effectiveness of technology-mediated learning (Sitzmann and Weinhardt, 2019; Nair *et al.*, 2017; Demir *et al.*, 2021; Fan *et al.*, 2023).

2.3 Technology adoption

Adoption of TML by learners is a prerequisite for it to be effective (Lv and Li, 2024); however, high levels of attrition have been observed in TML, negatively impacting its effectiveness (Sitzmann and Weinhardt, 2019; Fake and Dabbagh, 2021; Liu and Yu, 2023). In learning, attrition is defined as the loss of learners from a learning experience and is an outcome of disengagement (Huber *et al.*, 2023). Thus, many researchers have attempted to explore ways to encourage continued use of TML, including studying the role that technology adoption constructs can play in influencing the adoption of TML (Panigrahi *et al.*, 2018; Granić, 2023). Among various channels of TML, the adoption of eLearning has been the most often researched, followed by the adoption of mobile learning and the adoption of learning management systems (Granic, 2022).

UTAUT, a model proposed by combining key constructs of eight other technology adoption frameworks and later revised to include constructs that customize it for end-user adoption (UTAUT2), is one of the most popular technology adoption models (Tamilmani *et al.*, 2021; Venkatesh *et al.*, 2012). UTAUT2 has been used in different contexts and domains, including studies focusing on the adoption of online learning (Tamilmani *et al.*, 2021; Lv and Li, 2024), and has consistently reported higher explanatory power for intention to use and actual use of technology when compared to other technology adoption models, especially in the learning domain (Pan and He, 2024).

The UTAUT2 framework has seven independent constructs, namely, performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), price value (PV) and habit (H). These seven constructs impact use behavior (UB) through mediation by behavior intention (BI) (Arthur *et al.*, 2023). Performance expectancy (PE) relates to users' belief that using the technology will improve their performance. Effort expectancy (EE) reflects the users' perception of the ease with which they can use the technology (Singh *et al.*, 2023). Social influence (SI) represents the influence that important others have on an individual's decision to use a technology. Facilitating conditions (FC) refer to the users' perception of the support that's available to use the system. Hedonic motivation (HM) represents the fun or pleasure associated with the use of any technology. This is the intrinsic motivation associated with using a system and complements PE, which is the extrinsic motivation associated with the use of any technology (Venkatesh *et al.*, 2012). Their association with motivation makes PE and HM particularly important in the learning domain, as motivation is known to enhance learning effectiveness (Sitzmann and Weinhardt, 2019; Kapp *et al.*, 2020; Huber *et al.*, 2023). Price value (PV) is the monetary cost associated with the use of the technology. In a workplace learning context, PV isn't relevant, as learning technologies are sponsored by the employers and not the employees, who are the end users or learners. Habit (H) reflects the degree to which users believe the use behavior is automatic. Behavioral intention (BI) shows the users' intent to use the technology (Arthur *et al.*, 2023). Among all the independent constructs, PE has consistently been reported to have the strongest influence on BI, highlighting the importance accorded by individuals to a technology's utilitarian value (Chao, 2019; Venkatesh *et al.*, 2012).

The proponents of UTAUT2 have actively encouraged researchers to further extend it, especially by including constructs that reflect improved performance through technology use (Venkatesh *et al.*, 2016; Venkatesh, 2024). On these lines, Singh *et al.* (2023) and Lv and Li (2024) expanded the UTAUT model in the academic context and demonstrated that improved adoption leads to better learning outcomes. In the current study, we aim to build a model based on UTAUT2 that can enhance the adoption and effectiveness of TML in workplaces.

2.4 Personalization of learning

In workplaces, professionals pursue a variety of learning goals driven by factors such as personal interests, career goals and organizational objectives; however, they struggle to identify relevant learning resources as there are too many options (Hemmler *et al.*, 2023). Studies have shown that personalization can reduce cognitive load and increase perceived usefulness and motivation (Geng *et al.*, 2019; Bernacki *et al.*, 2021). Personalization of learning is defined as tailoring learning experiences to meet learners' needs and interests (Bernacki *et al.*, 2021). Personalization is typically based on two key components, namely, agents of personalization and parameters of personalization. Systems or individuals that play a role in personalizing learning are known as agents of personalization. At workplaces, these agents could be the individuals, their peers, leaders and learning systems. Agents personalize learning based on certain factors, such as learners' performance gaps, goals and interests. These factors are known as parameters of personalization. Most of the attempts to personalize learning in workplaces rely on leaders and learners customizing learning experiences based on employees' needs and preferences (Fake and Dabbagh, 2020). It's noteworthy that most research on personalization of learning has been conducted in educational set-ups, with limited studies in workplaces (Bernacki *et al.*, 2021; Fake and Dabbagh, 2020, 2023b). Further, the studies that have focused on personalized learning in workplaces have viewed it from learners' perspectives and there's a need to capture organizations' perspectives by gathering inputs from supervisors (Hemmler *et al.*, 2023). Through this study, we attempt to address this gap and identify personalization factors from individuals' and organizations' perspectives that can influence engagement of working professionals with their TML ecosystems, thereby improving its adoption and effectiveness.

2.5 Relationships between learning effectiveness, technology-mediated learning, technology adoption and personalized learning

The impact of personalization on learning effectiveness is well-established (Fake and Dabbagh, 2021); however, there are limited studies that have gone beyond adoption and studied the influence of technology adoption constructs on learning effectiveness (Lv and Li, 2024). Integrating insights from studies focusing on learning effectiveness, technology-mediated learning, technology adoption and personalized learning informs us that learners will be more willing to adopt TML and transfer training if they have supervisory support and have the flexibility to access learning resources that they perceive will positively influence their performance (Massenberg *et al.*, 2015; Panigrahi *et al.*, 2018; Fake and Dabbagh, 2021). In this study, we attempt a novel approach where we integrate constructs of personalization and constructs of UTAUT2 to explore their combined impact on the adoption and effectiveness of TML. This view is echoed by other researchers who have expressed that further investigation, including qualitative research, is needed to understand the complex relationships between various UTAUT constructs and learning effectiveness (Singh *et al.*, 2023; Lv and Li, 2024).

3. Methods

An exploratory sequential mixed-method approach was adopted to address the research questions, as there are limited studies available in the workplace context (Kumar *et al.*, 2019;

Issa *et al.*, 2023). The study began with semi-structured interviews of L&D leaders and employees of large organizations that practiced TML (Tables 1 and 2).

Both the leaders and employees, across the globe, were asked to share their views on the adoption and effectiveness of TML in their respective organizations, its challenges and how personalized TML may improve its adoption and effectiveness. Convenience and theoretical sampling were used to collect data (Makri and Neely, 2021). All the interviews were recorded, transcribed and later analyzed using NVIVO software. All narratives were coded using open coding, axial coding, selective coding and theoretical coding (Makri and Neely, 2021). All codes were accompanied by authors' memos to deepen our understanding of constructs and their interconnections. Coding and emergent themes were re-validated by the authors manually and individually, and any disparity was sorted out via discussions. Inputs from leaders and employees were compared and triangulated to gain deeper insights into existing practices around deployment and the use of TML. Emergent themes led us to our research model and set of hypotheses, which we tested through a cross-sectional study using partial least squares structural equation modeling (PLS-SEM).

For the cross-sectional study, we collected data from employees working in organizations that have already used TML and those with prior experience of using TML. We initially reached out to 1,500 employees, of which 550 met the aforementioned criteria. After removing the missing data, we found 406 complete responses, which were considered for further analyses (Table 3). As our study is exploratory and deals with a relatively complex model involving many constructs and relationships, we chose PLS-SEM, with the recommended bootstrap sample of 5,000, for data analysis (Hair *et al.*, 2019; Sarstedt *et al.*, 2022; Yıldız, 2022). PLS-SEM allows testing a framework from a predictive perspective and offers higher statistical power, which is quite useful for exploratory research (Hair *et al.*, 2019). PLS-SEM relies on bootstrapping, a non-parametric procedure, to determine statistical significance (Hair *et al.*, 2019; Ringle *et al.*, 2024). While bootstrapping is needed to determine statistical significance, it relies on good data, i.e. the sample is large enough and is a good approximation of the population (Streukens and Leroi-Werelds, 2016).

The qualitative analyses yielded seven constructs, which were measured with 23 items in Study 2. The items were adapted from multiple studies, the details of which are mentioned in Table 4. All the items were measured based on a 5-point scale, with 5 being the highest and 1 being the lowest. The details of constructs, their operational definitions, and measurement scales are presented in Table 4. The reliability and validity of the constructs are presented in the result section.

4. Results

4.1 Study 1: qualitative analyses and hypotheses development

The narratives were coded using the principles of grounded theory. Themes were identified from open codes, axial codes, selective codes and the author's memo. Figure 1 depicts the codification process. Selected codes are presented in Table 5. Three themes emerged from Study 1—Personalized learning, TML adoption and TML effectiveness, which enabled us to develop the research model with relevant constructs (Table 4) and their interconnections (Figure 2), leading to 11 statistical hypotheses proposed for Study 2.

4.1.1 Personalized learning impacting TML adoption. Two major personalizing parameters, namely PRM and EI&P, were evident in the narratives of the L&D leaders and employees (learners). Both groups expressed the relevance of managers recommending TML courses based on business and employee needs. For example, when the leaders were asked how to increase TML adoption, L1 opined:

> . . . right balance between allowing people the time that they need to learn but then also not overburdening them with learning that they don't need. So, the goal here is really to make sure that learners don't spend time on content that they already know, so the limited time that anybody in a corporate setting has to spend on learning in a world where everybody is really, really busy, they can focus it on what is relevant and what they need to learn and not just on a pre-determined piece of learning even though they might not really need that . . .

Table 1. Details of Study 1 participants [illegible])

Participant number	Participant location	Sect[illegible]	Designation	Gender	Generation	Experience (in years)	Office presence	Revenue	No. of employees
L1	Germany	Prof[illegible] Services	Learning Leader	Female	Gen X	20	Global	40 B USD	3,50,000
L2	Netherlands	Indu[illegible]istributor of S[illegible]es	Head Learning	Male	Gen Y	18	Global	1.5 B Euro	2,500
L3	India	IT	Learning Leader	Female	Gen X	21	Global	840 M USD	21,000
L4	India	Prof[illegible] Services	Head Learning	Female	Gen Y	21	US, India, Philippines	400 M USD	3,000
L5	US	Insu[illegible]	Head Learning	Female	Gen Y	19	US, India, Philippines	16 B USD	7,500
L6	India	Prof[illegible] Services	Manager Learning	Female	Gen Y	17	Global	50 B USD	3,50,000
L7	UK	Inve[illegible]Bank	Ex-VP Learning	Female	Gen Y	19	Global	2.5 B GBP	84,000
L8	Australia	Fina[illegible]rvices grou[illegible]	Ex-Head of Learning Design	Female	Gen Y	21	Global	11.2 B USD	17,000
L9	India	Tele[illegible]	Senior Manager, Learning	Male	Gen X	20	Global	22 B GBP	1,00,000
L10	Australia	Ene[illegible]npany	Operations Specialist	Male	Gen X	27	Global	15 B USD	10,000
L11	US	Inve[illegible]Bank	VP Talent	Female	Gen X	23	Global	20 B USD	2,31,000
L12	US	Prof[illegible] Services	Ex-Learning Leader	Male	Baby boomer	37	Global	40 B USD	3,50,000

Source(s): Authors

Table 2. Details of Study 1 participants … s/employees)

Participant number	Participant location	…	Seniority	Gender	Generation	Experience in years	Office presence	Revenue	No. of employees
E1	India	sional es	Junior	Female	Gen Y	15	Global	40 B USD	3,50,000
E2	Netherlands	sional es	Mid-level	Female	Gen X	22	Global	40 B USD	3,50,000
E3	Australia		Mid-level	Female	Gen Y	15	Global	212 M USD	3,000
E4	Poland	sional es	Mid-level	Male	Gen X	23	Global	40 B USD	3,50,000
E5	Australia	ES	Mid-level	Male	Gen Y	13	Global	600 M USD	6,000
E6	US	sional es	Senior	Female	Gen Y	19	Global	50 B USD	3,50,000
E7	Canada		Mid-level	Female	Gen Y	15	Global	50 B USD	97,000
E8	India		Senior	Male	Gen X	24	Global	3 B USD	8,200
E9	India	nce	Senior	Male	Gen Y	18	Global	130 B USD	1,45,000
E10	India		Mid-level	Female	Gen Y	13	Global	207 B USD	2,21,000
E11	India	nce	Junior	Female	Gen Y	12	Global	130 B USD	1,45,000
E12	US	sional es	Mid-level	Female	Gen X	20	Global	40 B USD	3,50,000
E13	China	sional es	Junior	Female	Gen Y	9	Global	40 B USD	3,50,000
E14	Australia	sional es	Senior	Female	Gen X	24	Global	40 B USD	3,50,000
E15	India	sional es	Mid-level	Female	Gen Y	18	Global	40 B USD	3,50,000

Source(s): Authors

Table 3. Details of Study 2 respondents

	Number of respondents	% of respondents		Number of respondents	% of respondents
Gender			*Sector*		
Male	197	48.50	IT & ITES	266	65.52
Female	202	49.80	Pharmaceutical	15	3.69
Prefer Not to Say	7	1.70	PS	38	9.36
Generation			Manufacturing	24	5.91
Baby Boomers (1946–1964)	7	1.72	Education	11	2.71
Gen X (1965–1980)	130	32.01	FMCG	7	1.72
Gen Y (1981–1995)	247	60.83	Healthcare	11	2.71
Gen Z (1996–2010)	22	5.42	Insurance	9	2.22
Years of experience			Others	25	6.16
0–5 years	33	8.10	*Size of the organization*		
5–10 years	60	14.80	Less than 100 employees	9	2.20
10–15 years	99	24.40	101–500 employees	11	2.70
15+ years	214	52.70	501–1,000 employees	13	3.20
Location (Continent)			1,001–5,000 employees	18	4.40
Africa	1	0.25	5,001–10,000 employees	35	8.60
Asia	306	75.37	10,001+ employees	320	78.80
Australia	8	1.97	*Management level*		
Europe	39	9.61	Senior Management	88	21.70
North America	52	12.81	Middle Management	190	46.80
Type of organization			Junior Management	128	31.50
Multinational (offices in more than 1 country)	384	94.60			
Domestic (offices in 1 country)	22	5.40			

Source(s): Authors

Thus, identifying need-based relevant resources is key to an employee's intention for TML adoption. The availability of too many TML options is considered to be a common challenge, as it increases the effort to find relevant resources, spurring employees to withdraw quickly from the learning path. Employees have limited time and need solutions that help them find relevant learning quickly and efficiently.

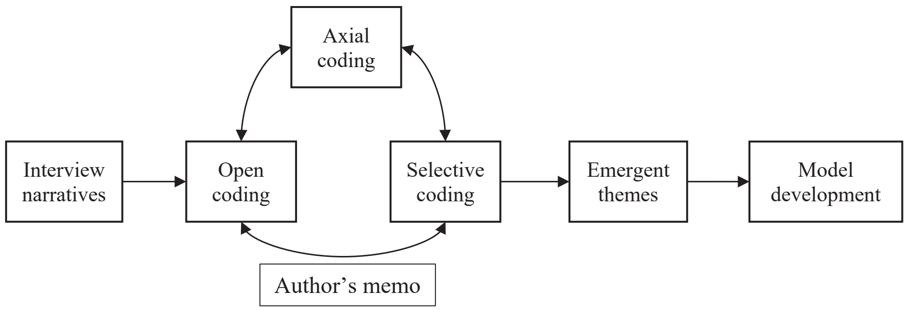
> L9: "... Imagine you enroll or sign up on Udemy. It tells you on the landing page we've got 20,000+ courses across domains, across your interests. Now I'm not in the job of the admin guy who will shuffle through papers and stack them. That's not value ...

Employees also opined on similar lines. They often found that, due to the absence of effective search functionality, the courses weren't aligned to their needs. Instead of going through generic courses, they would prefer receiving learning recommendations that are aligned with their goals and performance gaps, especially those that are recommended by their seniors or managers.

Table 4. Details of the constructs and scales

Constructs	Operational definition of constructs	No. of items	Item adapted from
Personalization constructs			
Personalization based on recommendations from Seniors and Managers a (PRM)	Managers- and seniors-provided personalized TML recommendations based on employee's performance gaps or future business goals	2	Brown *et al.* (2010), Martins *et al.* (2014), Chiu and Wang (2008)
Personalization based on employee's interest and preferences (EI&P)	Personalization that's based on employee's interests and preferences, including, when to learn, at what pace to learn and which devices, languages and media they would like to use to learn from TML	6	
Technology adoption (UTAUT 2) constructs			
Performance expectancy (PE)	PE focuses on the utilitarian value of TML	2	Venkatesh *et al.* (2012), Chao (2019)
Social influence (SI)	SI is the degree to which users perceive that important others believe they should consume TML	3	
Hedonic motivation (HM)	HM refers to the pleasure associated with use of TML	3	
Behavioral intention (BI)	BI is defined as the intention of employees to use TML	3	
Transfer of training constructs			
Transfer of training (TT)	Learners applying knowledge and skills gained from TML in real-world situations	4	Denan *et al.* (2020), Chen and Chen (2006), Santos and Stuart (2003), Bai *et al.* (2018), Rodríguez-Santero *et al.* (2020), Manju and Suresh (2011)

Source(s): Authors



Source(s): Authors

Figure 1. Codification process

Table 5. Codification

Respondents	Narratives	Open codes	Axial codes	Selective codes	Author's memo	Theme
E10	*And then also when there aspirations for future to g in a certain field, such programs also are recommended then by the reporting manager*	1. Learners' learning aspirations for future growth 2. Managers' recommendations for learners' learning aspirations	1. Performance expectancy (PE) 2. Leader – guided personalization	1. Performance Expectancy (PE) 2. Personalization based on recommendations from Seniors and Managers (PRM)	Personalized recommendations of the managers or seniors would improve performance expectations and thereby enhancing TML effectiveness	Personalized learning
L10	*And for example, my, uh, supervisor has a look of modules. As you might sa he would then identify so those modules along with our one – on – one and sa listen, I think this will be useful for you. Why don't go through and you know that module so that modu se is standard, but which module is picked for me be different for which mo is picked for you, so that my own personal develop*	1. Supervisor/manager recommended learning 2. Learning recommendations based on employees' own developmental needs	1. Performance expectancy (PE) 2. Leader – guided personalization 3. Employee's need-based personalization	1. Performance Expectancy (PE) 2. Personalization based on recommendations from Seniors and Managers (PRM)	Employees' personal development is performance dependent	Personalized learning
E10	*And the other point I wo add is from peers, that w there is a good training v is also recommended by peers or some teams*	1. Learning recommendations from peers based on their learning experiences	1. Peers – guided personalization	1. Personalization based on recommendations from Seniors and Managers (PRM) 2. Social influence (SI)	Peers often recommended courses which they have enjoyed or recommended by their seniors/managers/ team	Personalized learning

(*continued*)

Table 5. Continued

Respondents	Narratives	Open codes	Axial codes	Selective codes	Author's memo	Theme
E14	*But they might pick anoti one such as anti – briber that might go for exampl directors and above. So depending on your senio and then also your role. probably going to go to everybody in a client ser role or people working ir enterprise or business su like I am. Sometimes I dc notice that they are targe more senior people*	1. Role based learning recommendations from managers	1. Leader – guided personalization	1. Performance Expectancy (PE) 2. Personalization based on recommendations from Seniors and Managers (PRM)	Personalized recommendations of the managers or seniors would improve performance expectations and thereby enhancing TML effectiveness	Personalized learning

(*continued*)

Table 5. Continued

Respondents	Narratives	Open codes	Axial codes	Selective codes	Author’s memo	Theme
L1	*right balance between allowing people the time they need to learn, but th also not over – burdening with learning that they d need. So, the goal here is to make sure that learner don’t spend time on cont that they already know s the let’s face it limited tim anybody in a corporate s has to spend on learning world where everybody i really, really busy, that th can focus it on what is rel and what they need to le and not just on a predetermined piece of learning even though the might not really need tha*	1. Balancing employee preferred time and relevant learning content 2. Avoiding repeat content for learning 3. Employee need-based learning	1. Preferred timing for learning 2. Employee need-based learning	1. Personalization based on employee’s interest and preferences (EI&P) 2. Performance expectancy (PE)	Employee preferences would enhance their motivation thereby improving TML continuity and effectiveness	Personalized learning and TML adoption

(*continued*)

Table 5. Continued

Respondents	Narratives	Open codes	Axial codes	Selective codes	Author's memo	Theme
E4	*I think managers, as wel business leaders, when th looking for someone to jo project, the requirements kind of clearly stated or reading the description y may quite easily find out will be expected from you and well either you have skills and experience or n you can partially fit into position and some areas c upskilled*	1. Recommending learning based on project needs 2. Allowing learners to be upskilled	1. Business need-based learning	1. Personalization based on recommendations from Seniors and Managers (PRM) 2. Performance expectancy (PE)	Personalized recommendations of the managers or seniors would improve performance expectations and thereby enhancing TML effectiveness	Personalized learning and TML adoption
L3	*A few months back we launched the project management initiative in particular vertical, the ir measure for that was tha example of people got deployed into roles which require them to be dealing situations of project management. So you hav some parameters which c business linked or you kn movement or rotation lin parameters*	1. Recommending learning based on project needs 2. Allowing learners to be upskilled for new role	1. Business need-based learning 2. Employee need-based learning	1. Personalization based on recommendations from Seniors and Managers (PRM) 2. Performance expectancy (PE)	Personalized recommendations of the managers or seniors would improve performance expectations and thereby enhancing TML effectiveness	Personalized learning and TML adoption

(*continued*)

Table 5. Continued

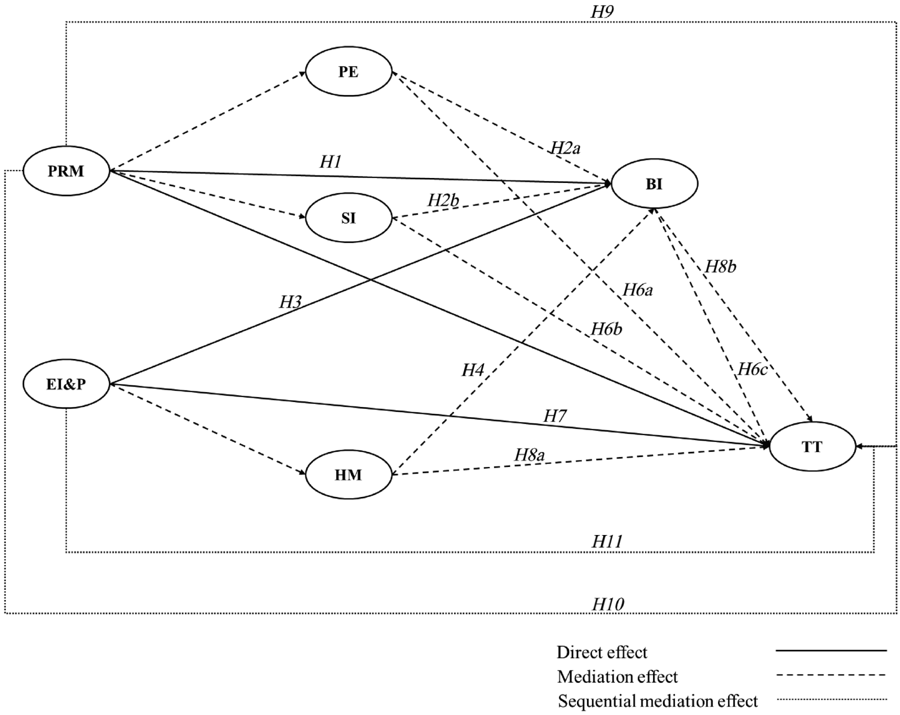
Respondents	Narratives	Open codes	Axial codes	Selective codes	Author's memo	Theme
L5	*Using the people on the gı to give that feedback anc give us that insight of ho they're applying it. So fo every single Academy th have at our organization whether it's Manager Academy or the Leadersl Training or Underwritin Claims or whatever, we l very, very well formed St Cos and project teams aı councils, and we use ther sounding board to see – the learning is being roll out? How is it being embedded? And their goa create the feedback loop needed to make sure that on path and to also creat some of the data, the stoı behind the data*	1. Receiving feedback from the managers about applying learning knowledge 2. Monitoring post-training performance	1. Learning application 2. Providing leaning feedback	1. Transfer of training (TT)		TML effectiveness

(*continued*)

Table 5. Continued

Respondents	Narratives	Open codes	Axial codes	Selective codes	Author's memo	Theme
L5	*So when I look at the KP that particular path, it's n that they attended the tra and the NPS and all that, we actually look at – Did write more business? Dic do more cross sell? Were more profitable as an organization if we taught how to do the portfolio management? Did we see increase on the profitabil there? And we look at th data components knowin you know the learning is n only thing that's contribut that, but can we look at a those data elements in an non – biased way to reall create the story?*	1. Measuring learning effectiveness through assessing pre – an post – training business KPIs or profitability	1. Learning effectiveness	1. Transfer of training (TT)		TML effectiveness
L8	*We reported on return or expectations (ROE), whi these are the expectation we had more of an ROE based framework, than a – based framework keep mind expectations equal organizational objective the understanding there you're meeting organiza objectives, you are gener return on investment*	1. Measuring learning effectiveness through return on expectations or expected outcomes	1. Learning effectiveness	1. Transfer of training (TT)		TML effectiveness

Source(s): Authors



Source(s): Authors

Figure 2. Research model with hypotheses

> E3: "… what I have personally experienced and what 90% of the people I have seen around me experience is – they do not tailor it to user groups. So, everybody who comes into the system needs to take those 16–17 hours of product and pricing, competition, and feature training, which is not even relevant to their job. So, it comes up like a click-and-forward sort of action in terms of learning …"

> E10: "… when there are aspirations for future growth in a certain field, such programs also are recommended by the reporting manager …"

Employees also preferred to have flexibility in choosing what, when and how they want to learn.

> E1: "… So when I'm traveling, if I see I have some time and I can spend some time on learning … … I can see some small videos or the nuggets … … I use phone …"

> E6: "… I can interact with it based on my schedule. So, if I start it in the morning, hit a couple of meetings, I can pause it and come back to it. And if there's something that I felt like I tuned out when they were going over, I can record it and skip back to it and review that section. So, I feel like just from a perspective of it fitting well into being able to complete work and access the learning when I need it, I really like it …"

Both leaders and employees indicated that personalized recommendations from managers and peers that align with their performance gaps and goals may improve TML adoption. Likewise, employee preferences, namely, when, where and at what pace they learn, choice of media and devices on which they learn, would further facilitate TML adoption. Thus, we hypothesized:

H1. The direct effect of PRM on BI will be significant.

H2. The indirect effect of PRM on BI via (a) PE and (b) SI independently will be significant.

H3. The direct effect of EI&P on BI will be significant.

H4. The indirect effect of EI&P on BI via HM will be significant.

4.1.2 Personalized learning impacting transfer of training (TT). When leaders and employees were asked to share their views on TT, both echoed a similar line reflecting the relevance of personalized learning in enhancing TT. For example,

L10: ". . . and for example, my supervisor has a look at modules. As you might say, and he would then identify some of those modules along with us in our one-on-one and say, hey listen, I think this will be very useful for you. Why don't you go through and you know do that module so that module *per se* is standard, but which module is picked for me might be different for which module is picked for you, so that is in my own personal development . . ."

E4: ". . . I think managers, as well as business leaders, when they're looking for someone to join the project, the requirements are kind of clearly stated, or by reading the description, you may quite easily find out what will be expected from you to do, and well, either you have those skills and experience, or maybe you can partially fit into this position and some areas can be upskilled . . ."

Undoubtedly, personalized recommendations from managers and seniors based on employees' current and future needs help align employees with their personal and organizational goals and consequently enhance their BI and TT. Thus, we hypothesize:

H5. The direct effect of PRM on TT will be significant.

H6. The indirect effect of PRM on TT via (a) PE, (b) SI and (c) BI independently will be significant.

H7. The direct effect of EI&P on TT will be significant.

H8. The indirect effect of EI&P on TT via (a) HM and (b) BI independently will be significant.

H9. The indirect effect of PRM on TT via PE and BI sequentially will be significant.

H10. The indirect effect of PRM on TT via SI and BI sequentially will be significant.

H11. The indirect effect of EI&P on TT via HM and BI sequentially will be significant.

4.2 Study 2: quantitative analyses

4.2.1 Measurement model. A PLS-SEM was conducted to test the hypotheses with a bootstrap sample of 5,000. Table 6 describes the details of the measurement model. Findings related to constructs' reliability and validity were found to be acceptable (Cheung *et al.*, 2023).

The Fornell–Larker criterion was used to measure discriminant validity, and the AVE of each construct was higher than its squared correlation with all other constructs (Table 7). Further, when cross-loadings were examined, each indicator's load was found to be highest on the construct it was intended for, demonstrating acceptable levels of discriminant validity (Cheung *et al.*, 2023). We also checked the common method variance (CMV) using Harman's Single Factor Test. SPSS AMOS was used to calculate the same. The test estimated a shared variance between all the items at 32%, below the classic threshold of 50% as suggested by Harman (1960). This indicated that the CMV didn't influence our findings significantly (Kock *et al.*, 2021).

Table 6. Construct reliability and convergent validity

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)	Loadings
PRM	0.734	0.737	0.883	0.790	2 items; 0.88–0.90
EI&P	0.923	0.930	0.940	0.725	6 items; 0.74–0.91
PE	0.885	0.885	0.946	0.897	2 items; 0.94–0.94
SI	0.893	0.895	0.933	0.824	3 items; 0.89–0.93
HM	0.858	0.870	0.913	0.778	3 items; 0.84–0.92
BI	0.907	0.908	0.942	0.844	3 items; 0.89–0.94
TT	0.868	0.881	0.910	0.717	4 items; 0.76–0.90

Source(s): Authors

Table 7. Discriminant validity

Construct	PRM	EI&P	PE	SI	HM	BI	TT
PRM	0.889						
EI&P	0.205	0.852					
PE	0.471	0.216	0.947				
SI	0.446	0.217	0.527	0.908			
HM	0.411	0.298	0.665	0.509	0.882		
BI	0.466	0.274	0.753	0.481	0.612	0.919	
TT	0.517	0.236	0.644	0.580	0.687	0.622	0.847

Note(s): Squared correlations; AVE in the diagonal
Source(s): Authors

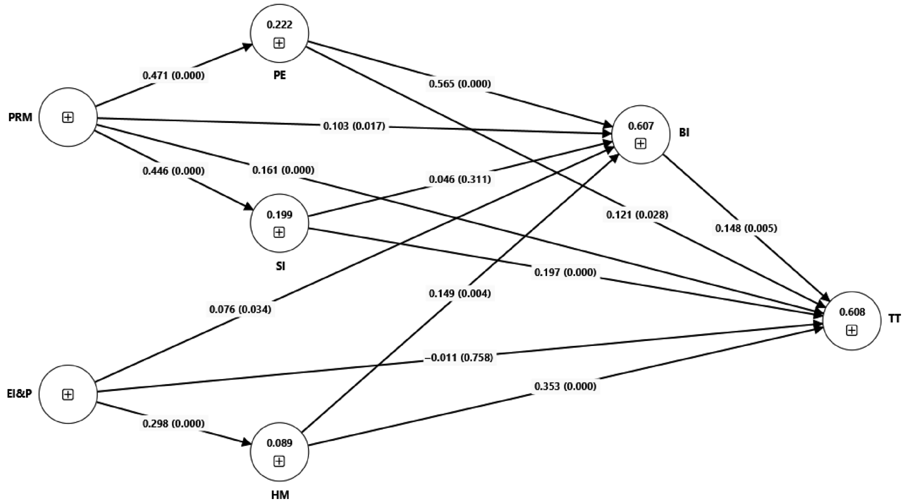
4.2.2 Structural model. Path analyses (Figure 3) revealed that PRM, EI&P, PE, SI and HM together accounted for 60.7% of the variance of BI ($R^2 = 0.607$); and PRM, EI&P, PE, SI, HM and BI together accounted for 60.8% of the variance of TT ($R^2 = 0.608$). Both models display fairly high explanatory power (Hair *et al.*, 2019).

The results of multiple mediators (both independent and sequential) reflected that:

(1) The direct effects of PRM to BI ($\beta = 0.103$; $p < 0.05$); PRM to TT ($\beta = 0.161$; $p < 0.001$); and EI&P to BI ($\beta = 0.076$; $p < 0.05$) were found significant; however, EI&P to TT ($\beta = -0.011$; $p > 0.05$) was not significant. Thus, H1, H3, H5 were accepted, and H7 was rejected.

(2) The indirect effects, namely, PRM to BI via PE ($\beta = 0.266$; $t = 6.979$; $p < 0.001$); EI&P to BI via HM ($\beta = 0.044$; $t = 2.363$; $p < 0.05$); PRM to TT via PE ($\beta = 0.057$; $t = 2.138$; $p < 0.05$); PRM to TT via SI ($\beta = 0.088$; $t = 3.950$; $p < 0.001$); EI&P to TT via HM ($\beta = 0.105$; $t = 3.782$; $p < 0.001$); PRM to TT via PE and BI sequentially ($\beta = 0.039$; $t = 2.614$; $p < 0.01$) were found significant, thus, H2a, H4, H6a, H6b, H8a and H9 were accepted. However, H2b, H6c, H8b, H10 and H11 were rejected.

The detailed results of total effects, direct effects and indirect effects are presented in Tables 8 and 9, respectively.



Source(s): Authors

Figure 3. Results of the structural equation model

Table 8. Total effects

Effects	Path result	Standard bootstrap results Sample mean (M)	Standard deviation (SD)	*t* value	*p* values (2-sided)
PRM → PE	0.471	0.471	0.046	10.262	0.000
PRM → SI	0.446	0.445	0.045	9.831	0.000
PRM → BI	0.390	0.389	0.052	7.518	0.000
PRM → TT	0.363	0.362	0.042	8.587	0.000
EI&P → HM	0.298	0.300	0.065	4.580	0.000
EI&P → BI	0.121	0.121	0.042	2.865	0.004
EI&P → TT	0.112	0.114	0.043	2.612	0.009
PE → BI	0.565	0.565	0.057	9.821	0.000
PE → TT	0.204	0.203	0.048	4.298	0.000
SI → BI	0.046	0.046	0.045	1.013	0.311
SI → TT	0.203	0.203	0.044	4.663	0.000
HM → BI	0.149	0.146	0.052	2.866	0.004
HM → TT	0.375	0.377	0.049	7.598	0.000
BI → TT	0.148	0.147	0.053	2.821	0.005

Source(s): Authors

5. Discussion

Most of the global firms are reporting growing interest and investment in TML (Gartner, 2022), but despite organizations' growing interest, employees' apathy toward TML adoption has limited its effectiveness, raising concerns about its use (Sitzmann and Weinhardt, 2019). Previous studies have highlighted design issues resulting in a lack of a learner-centric approach, which has led to reduced engagement and motivation, causing high drop-out rates (Fake and Dabbagh, 2021). We attempt to address these issues in this study through the lens of personalization of learning and technology adoption. This study seeks to address two vital questions pertaining to workplace learning in today's digital era: *whether and how (1) personalization of learning can improve adoption and continued use of technology-mediated*

Table 9. Direct and indirect effects

Effect	Path result	Standard bootstrap results Sample mean (M)	Standard deviation (SD)	t value	p values (2-sided)
Direct Effects					
PRM → PE	0.471	0.471	0.046	10.262	0.000
PRM → SI	0.446	0.445	0.045	9.831	0.000
PRM → BI	0.103	0.103	0.043	2.384	0.017
PRM → TT	0.161	0.161	0.037	4.326	0.000
EI&P → HM	0.298	0.300	0.065	4.580	0.000
EI&P → BI	0.076	0.077	0.036	2.122	0.034
EI&P → TT	−0.011	−0.010	0.035	0.308	0.758
PE → BI	0.565	0.565	0.057	9.821	0.000
PE → TT	0.121	0.121	0.055	2.203	0.028
SI → BI	0.046	0.046	0.045	1.013	0.311
SI → TT	0.197	0.196	0.043	4.556	0.000
HM → BI	0.149	0.146	0.052	2.866	0.004
HM → TT	0.353	0.355	0.050	7.016	0.000
BI → TT	0.148	0.147	0.053	2.821	0.005
Indirect effects					
PRM → PE → BI	0.266	0.266	0.038	6.979	0.000
EI&P → HM → TT	0.105	0.107	0.028	3.782	0.000
PRM → SI → TT	0.088	0.088	0.022	3.950	0.000
EI&P → BI → TT	0.011	0.011	0.006	1.778	0.075
EI&P → HM → BI → TT	0.007	0.007	0.004	1.737	0.082
PRM → PE → TT	0.057	0.057	0.027	2.138	0.033
HM → BI → TT	0.022	0.022	0.011	1.941	0.052
PRM → SI → BI → TT	0.003	0.003	0.004	0.859	0.391
PE → BI → TT	0.084	0.083	0.031	2.743	0.006
PRM → BI → TT	0.015	0.015	0.009	1.753	0.080
PRM → PE → BI → TT	0.039	0.039	0.015	2.614	0.009
SI → BI → TT	0.007	0.007	0.008	0.875	0.381
EI&P → HM → BI	0.044	0.044	0.019	2.363	0.018
PRM → SI → BI	0.020	0.020	0.020	0.997	0.319

Source(s): Authors

learning (TML) among employees of business organizations and (2) personalized learning influences the transfer of knowledge and skills gained from TML.

During interviews, leaders and employees informed us that availability of too many options was the biggest problem with TML, as it made finding relevant resources a time-intensive task. They told us this is the biggest reason employees discontinue the use of TML, as time is a scarce commodity for most professionals. Too many options resulting in high cognitive overload and lack of time have been cited in the literature as barriers to learning that result in attrition (Fake and Dabbagh, 2021; Hemmler *et al.*, 2023). Learner attrition not only impacts utilization of learning resources but also hinders the upskilling of employees (Sitzmann and Weinhardt, 2019). Further, leaders and employees mentioned that personalizing learning based on employees' needs and interests can help address this challenge, and this is in line with the existing literature (Fake and Dabbagh, 2020; Bernacki *et al.*, 2021; Hemmler *et al.*, 2023). Such personalization would point learners toward a limited set of relevant resources, which would increase engagement and motivation, along with saving their time and effort in searching for suitable resources (Fake and Dabbagh, 2021).

Our findings from the quantitative study confirmed the proposed model and the associated propositions, i.e. the two personalization factors, namely PRM and EI&P, boost TML's effectiveness in workplaces by improving its adoption and transfer of training through direct and indirect pathways. Among all relationships in our model, the pathway of PRM to BI through PE had the largest effect, with PE being the strongest predictor of BI. This is in line with existing literature on UTAUT, highlighting the importance that learners associate with adopting technology that they believe will improve their performance (Ain *et al.*, 2016; Chao, 2019). Supervisors are well-placed to know the strengths and weaknesses of team members, so personalized TML recommendations from managers/seniors (PRM) help employees improve their performance and realize their future goals (Fake and Dabbagh, 2020), and hence PRM promotes TML adoption, i.e. reduces attrition. Contrary to our expectations and previous UTAUT literature (Singh *et al.*, 2023), social influence (SI) didn't have a significant influence on BI. A possible explanation for this could be that PE overshadowed the influence of SI on BI. Furthermore, PRM's influence on TT through direct as well as mediated pathways was found to be significant. This too is in line with existing literature where supervisory support has been reported to promote the transfer of training (Salamon *et al.*, 2021; Kim *et al.*, 2019; Pilbeam and Karanikas, 2023). Digitization usually reduces the human element from an employee's experience impacting trust (Randolph-Seng *et al.*, 2024), and performance-enhancing personalized recommendations from managers reinforce the message that employees have supervisory support. In workplaces, employees' performance determines the benefits and growth they receive. Therefore, personalized recommendations from managers/seniors can address both problems associated with TML, i.e. high attrition and low transfer rates, as employees will be eager to consume and transfer learning that can improve their performance and support their growth.

Further, our data shows that when employees' interests and preferences (EI&P) are taken care of while designing TML ecosystems, it positively influences their intention to use them. This influence is direct as well as mediated through hedonic motivation. Previous studies have reported similar findings, i.e. increased motivation leads to enhanced engagement and continued use (Huber *et al.*, 2023). In addition, an increase in employees' motivation to learn further encourages the transfer of training (Ford *et al.*, 2018; Nafukho *et al.*, 2023). Our findings show that EI&P's influence on TT is mediated via HM and BI, which is in line with previous research on learning and transfer (Grossman and Salas, 2011; Lv and Li, 2024; Bhat *et al.*, 2022). Employees prefer flexibility, and TML systems that support such needs promote learning and transfer (Fake and Dabbagh, 2021; Nafukho *et al.*, 2023).

Our research model explained 60.7% of the variance in behavioral intention (BI) and 60.8% of the variance in transfer of training (TT), confirming that personalized recommendations from seniors and managers (PRM), along with the flexibility to choose learning based on interests and preferences (EI&P), positively influence adoption of TML and transfer of training among working professionals (Fake and Dabbagh, 2020; Ford *et al.*, 2018; Gronseth and Hutchins, 2019), thus can improve the overall effectiveness of TML ecosystems (Sitzmann and Weinhardt, 2019).

Our study expands knowledge in a relatively nascent field of research, i.e. personalization of learning in workplaces, and addresses a key challenge that learning and development practitioners face, i.e. limited effectiveness of TML. We offer a novel process model that extends the UTAUT2 framework by integrating constructs of personalization and transfer of training to address the primary issues associated with TML, i.e. high attrition and low transfer rates. The model exhibits different pathways to enhance learning effectiveness by improving adoption (BI) and transfer (TT). It is important to highlight that our study focuses on the intention of learners to use TML and transfer learning instead of actual use or transfer. This is because ours is a cross-sectional study, proposing a futuristic model that organizations haven't implemented yet. That being said, it's well established that behavioral intention and intention to transfer are significant predictors of actual use and transfer, respectively (Xie *et al.*, 2024; Yang and Watson, 2020; Jeyaraj *et al.*, 2023). Findings from our research offer insights that L&D researchers and workplace practitioners can act upon. Researchers can assess our model in different cultural and geographical contexts. Furthermore, they can extend our model by adding new exogenous or endogenous constructs. Regarding implications for practice, our model and findings can guide L&D practitioners to design more effective TML ecosystems to address the challenges of high attrition and low transfer rates (Sitzmann and Weinhardt, 2019). This is of significant importance, as organizations are investing billions of dollars in training and development to support the evolving upskilling needs of their employees (Fake and Dabbagh, 2021; Singh *et al.*, 2023). However, they are unable to realize the full potential of their TML ecosystem, as learners are disengaging from these systems. By designing learner-centric TML systems, practitioners will be able to encourage continued use of TML and transfer of training. Systems that allow learners to receive performance-enhancing support from supervisors in the form of personalized recommendations can help learners perform, grow and get closer to their career goals. Further, conceiving systems that offer flexibility to learners will make learning enjoyable and allow professionals to accommodate learning in their busy work schedules. By offering such personalized experiences, L&D practitioners will be able to encourage adoption, learning and transfer, which will lead to improved performance and growth of individuals and businesses, and that's the end goal of all upskilling initiatives in business organizations.

6. Conclusion

TML is here to stay, as an increasing number of business organizations have started offering remote working opportunities to their employees. Therefore, organizations must address the challenges associated with TML so they can realize all the benefits associated with TML, such as cost reduction and improved geographical reach. High attrition rate is the most common issue associated with TML, and lack of relevance and lack of motivation are the two primary reasons causing these high levels of dropouts. Our study's primary goal was to identify ways to encourage adoption of TML, along with the transfer of knowledge and skills gained from TML, in business organizations. Specifically, we explored an area of research that has received scant attention from researchers, i.e. personalization of learning at workplaces and its influence on adoption of TML and transfer of training.

Our findings led us to several conclusions. First, personalized recommendations from seniors and managers encourage adoption of TML and transfer of training. Personalized recommendations from managers ensure learning is relevant, and such involvement of managers in employees' learning journey reflects their interest in team members' growth and development, which encourages employees to learn and apply newly gained skills. Second, flexibility to choose what, when and where to learn helps employees select learning that's aligned to their goals and allows them to accommodate learning in their busy schedules. Thus, it too encourages adoption and transfer of training.

7. Limitations and future research

The primary limitation of our study is that it's cross-sectional and relies on self-reporting by participants of their intent to use a TML system that personalizes their learning experiences based on their needs and interests and then transfer the learned knowledge and skills. We encourage future researchers to conduct longitudinal studies where they can report real-world data demonstrating the impact of such personalization on actual adoption and transfer of training. In addition, researchers can expand our model by including other personalization factors, such as personalization based on job profile or learning history.

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