Computers in Human Behavior Reports 18 (2025) 100680

Contents lists available at ScienceDirect

Computers in Human Behavior Reports

journal homepage: www.sciencedirect.com/journal/computers-in-human-behavior-reports

How do they like it? Higher education teachers' professional development preferences for blended learning and technology acceptance profiles

Anja Garone[a], Sarah K. Howard[b,d,*], Jie Yang[c], Jo Tondeur[d], Bram Pynoo[e], Bram Bruggeman[d,g], Katrien Struyven[f]

[a] Faculty of Psychology and Education, Vrije Universiteit Brussel, Pleinlaan 2, 1050, Brussels, Belgium
[b] School of Education, University of Leeds, Leeds, LS2 9JT, United Kingdom
[c] Faculty of Engineering and Information Sciences, School of Computing and Information Technology, University of Wollongong, Wollongong, NSW, 2522, Australia
[d] Vrije Universiteit Brussel, Multidisciplinair Instituut Lerarenopleiding, Brussels Research Institute for Teacher Education, Pleinlaan 2, 1050, Brussels, Belgium
[e] Education Policy Department, VIVES University of Applied Sciences, Doorniksesteenweg 145, 8500, Kortrijk, Belgium
[f] UHasselt Research on Innovative and Society-engaged Education (U-RISE), School for Educational Studies, Hasselt University, Martelarenlaan 42, 3500, Hasselt, Belgium
[g] Teacher Education Department, Secondary Education, Artevelde University of Applied Sciences, Kattenberg 9, 9000, Gent, Belgium

ARTICLE INFO

Keywords:
Professional development
Higher education
Teaching staff
Blended learning
Data mining
Association rules analysis

ABSTRACT

Blended learning is useful in higher education for catering to diverse student learning needs, however, higher education teaching staff need to be trained and supported so that it is applied attentively. Higher education teachers are diverse themselves with complex professional development needs. This study aims to examine the relationships between professional development preferences and 217 teaching staff grouped into technology acceptance profiles: high, moderate and low. Association rules analysis was run on an 18-item questionnaire dataset of the teaching staff's professional development preferences for blended learning. Results show that the high group is highly motivated to professionalise themselves collaboratively with added central support. The moderate group prefers centrally organised and guided professional development initiatives. The low group prefers centrally organised initiatives with guidance as well as incentive for professionalisation. These results highlight the differences between the groups, and how these preferences can be useful for designing targeted initiatives along with adapted communication strategies for groups with different technology acceptance levels.

1. Introduction

Blended learning (BL) is considered to be a solution for solving challenges in the organisation of higher education, eg. providing flexibility to students (Boelens et al., 2018; Garrison & Kanuka, 2004), and has been associated with improved student learning outcomes (Bohle Carbonell et al., 2013; Siemens et al., 2015). Online and BL approaches have furthermore been widely used in order to ensure continuation of education during the COVID-19 pandemic lockdowns (UNESCO IESALC, 2020).

Since the COVID-19 pandemic, the literature on BL in higher education and professional development (PD) for teaching staff has increased exponentially (eg. Zawacki-Richter, 2021). This means there is a significant need to re-examine the approach and methods for training and professionalising higher education teaching staff to meet the digitalization needs of higher education in the current climate (Scherer et al., 2021). However, one of the main challenges remains that technology anxiety still poses a significant barrier to change in teaching practices and the effective use of educational technology. While clustering users according to their technology acceptance and attitudes is a useful step towards understanding their technology acceptance needs, a closer look at these profiles is needed to understand how to approach these groups (AUTHORS; AUTHORS). This is particularly important for the groups who are less enthusiastic about educational technology, which is often related to technology anxiety and general risk-aversion (Howard, 2013).

Much is known about how to design PD for BL that is effective and sustainable (Philipsen et al., 2019), but little is known regarding how to

* Corresponding author. School of Education, University of Leeds, Leeds, LS2 9JT, United Kingdom.
E-mail addresses: anja.garone@vub.be (A. Garone), s.k.howard@leeds.ac.uk (S.K. Howard), jiey@uow.edu.au (J. Yang), jo.tondeur@vub.be (J. Tondeur), bram.pynoo@vives.be (B. Pynoo), bram.bruggeman@vub.be (B. Bruggeman), katrien.struyven@uhasselt.be (K. Struyven).

https://doi.org/10.1016/j.chbr.2025.100680
Received 8 November 2022; Received in revised form 26 April 2025; Accepted 27 April 2025
Available online 10 May 2025

adapt this design or approach to the characteristics of the participants. This study takes a closer look at how different groups of higher education teaching staff want to professionalise themselves for BL. PD models and approaches are examined and how they can serve different purposes. Technology acceptance as a relevant construct for PD for BL is explored and how it connects to person-centred research methods. Finally educational-datamining methods are discussed and how this approach can reveal useful information on group behaviours and characteristics.

1.1. Models of continuous professional development

Continuous PD, workplace learning, lifelong learning and in-service training are all internationally recognized keywords that have become part of the national policies and legislatures of OECD countries regarding education and training (Fraser, 2007; Swaffield, 2014). Regardless of how PD is organised, approached, and regulated, the intended outcomes of such initiatives are thought to benefit students, as well as the teaching staff themselves (Fraser et al., 2007; Guskey, 2002; Swaffield, 2014). On a policy level, PD initiatives answer the need for the regulation of standards and assurance of the quality of education on various levels in educational systems (Swaffield, 2014). The effects of PD on teachers and students is discussed in detail by Desimone (2009) whose foundational framework lists the key elements involved in PD design and execution, while evaluation of PD, for instance, is discussed in Guskey's (2000) five level evaluative framework. Design and evaluation are thus considered to be key pillars essential to the implementation of PD initiatives (Merchie et al., 2018). What is a "good" approach to PD, in general, is still a matter of debate, nevertheless it is agreed that depending on the context, different approaches to PD are suited for different types of contexts; eg. a short hands-on workshop is enough to teach practical skills regarding the use of a new technological tool, but transformative approaches such as collaborative professional inquiry are thought best suited where deep and meaningful transformation of beliefs and teaching practices are required (Kennedy, 2014).

In higher education settings, PD outcomes are dependent on many factors, such as the content of the PD and how relevant it is to specific disciplines (Díaz et al., 2010). Studies show that various context, such as content or discipline have an effect on how teachers use and implement technology in their teaching practices (Ding et al., 2019). Examples of discipline-specific relevance can be observed in several studies (e.g. Bingimlas, 2009; Garrison & Vaughan, 2013; Pérez-Foguet et al., 2018), where PD content and approaches were adapted to various contexts in the respective higher education institutions that were involved in the studies. Kennedy (2014) describes continuing PD both as a pedagogical and policy construct, in that it is intended to facilitate the learning of new knowledge and skills by teaching staff, while also being shaped by institutional as well as national decision-making bodies. Key components of continuing PD, according to Kennedy (2014), are teacher agency and autonomy and are used as a spectrum measure within the framework, where on the one end, transmissive models allow for the least amount of autonomy which increases on the other end with transformative models where the most autonomy and agency in participating teaching staff is encouraged. While the framework mostly serves as an indicator or guide for understanding how policy at different levels shape various PD initiatives in education (see Fig. 1.), it can also be used, in Kennedy's own words to "help us analyse patterns and trends in our own CPD experiences as individuals and to analyse institution-wide and system-wide approaches." (Kennedy, 2014, p. 694).

1.2. Technology acceptance

An important issue to be addressed with BL is technology acceptance, because the extent to which users of educational technologies accept these technologies also determines their attitudes towards applying them for BL (Bingimlas, 2009; Dias & Diniz, 2012; Surry et al., 2005). Technology acceptance can be measured as a construct with several determinants that result in predicting participants' intention and actual usage of a technology (Venkatesh et al., 2003). There are several scales that are useful to measure technology acceptance. One that has widely been implemented in educational settings is the unified theory for acceptance and use of technology by Venkatesh and colleagues (2003). The framework (see Fig. 2) consists of four main constructs: effort expectancy (perceiving the technology as easy to use), performance expectancy (perceiving the technology as useful), social influence (how the opinions and pressure from important peers influence the users' perception of the technology) and facilitating conditions (how well the users feel supported in different factors towards using the technology).

These scales are useful not only in determining what factors can ultimately predict use, but can also show researchers which groups of users will take up usage and how (Villani et al., 2018). Authors et al. (2019) found that by clustering university teaching staff according to how they scored in the four main UTAUT constructs, distinctly different groups are revealed that show differing levels of technology acceptance independent of moderating variables such as age and gender. Understanding the technology acceptance profiles of university teaching staff is a first step towards understanding how to approach these different groups in PDI's, and how to tailor PDI approaches to suit the needs and preferences of these groups.

High technology acceptance in education is associated with quick uptake and positive attitudes towards new technological tools (Pynoo et al., 2011a). Teaching staff with low technology acceptance also have higher anxiety towards technology and therefore resist using new tools and in general prefer not to change teaching practice (Schoonenboom, 2014; Wilfong, 2006). Teaching staff who are resistant to new technologies in general tend to avoid risks in teaching practice (Howard, 2013). Individuals who are resistant to change will often be present in every institute or organisation (Hall & Hord, 1987; Rogers, 2003), addressing the needs of these groups becomes a particular challenge when promoting and implementing BL in higher education (Ertmer, 1999; Howard, 2013). Understanding the differences between different groups

Model Purpose	Teacher agency & autonomy	Example of PD approach
Transmissive	Least	Training model Deficit model Cascade model
Malleable	↓	Award-bearing model Standards-based model Coaching-mentoring model Community of practice model
Transformative	Most	Collaborative professional inquiry model

Fig. 1. Models of continuing professional development, based on the original framework (Kennedy, 2014).

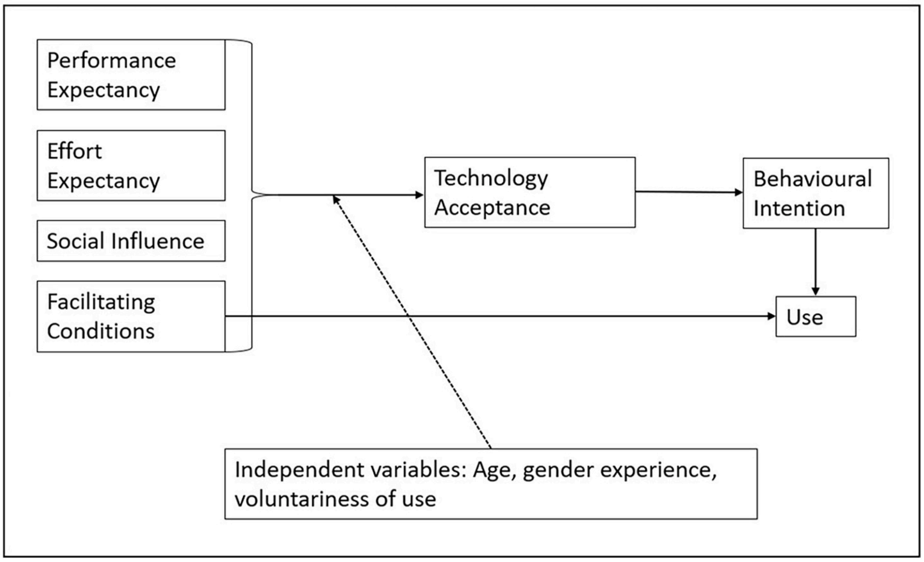


Fig. 2. The UTAUT model based on the original framework by Venkatesh et al. (2003).

of teaching staff, therefore, becomes an important component in devising tailored strategies for PD organisation (AUTHORS).

1.3. Person-centred research and data mining methods

Psychometric studies are normally variable-centred, meaning the aim is to define variables that describe homogenous populations regardless of their surrounding contexts (Hofmans et al., 2020; Morin et al., 2018). In person-centred research, the main goal is to break down participants into similar groups or profiles and to address the needs of these groups based on their profiles, rather than generalized variables (Hofmans et al., 2020; Weiss & Rupp, 2011). Person-centred methods such as clustering and latent profile analyses are considered to be well suited for studying phenomena among individuals in an occupational or working environment (Weiss & Rupp, 2011). Organising workplace learning opportunities and PD at a higher education institute is challenging first because of the many disciplines housed under the same institute, and secondly because of the variety of personal and professional contexts in which teaching staff is situated (Dysart & Weckerle, 2015). While clustering as an analytical method provides an opportunity to explore the characteristics of groups and subpopulations, a major pitfall that can occur is "hard clustering" in which participants are forced into certain group memberships more or less based on the best fit or similarities, thus causing some subpopulations to remain unobserved (Hofmans et al., 2020).

While understanding the differences between groups, educational data mining can further reveal attributes and patterns within groups and populations (Howard et al., 2016, 2021; Tondeur et al., 2021). Educational data mining is by now a well-established methodology in educational research, particularly as a method for capitalising on sources of educational data such as learning management systems and large-scale educational assessment studies (Baker, 2010; Merceron et al., 2015). Educational data mining offers several methods, among them is association rules analysis, a relationship mining method, which is the inductive analysis of relationship patterns among variables, which is frequently used in retail and marketing research for uncovering consumer preference patterns (Baker, 2010). The patterns in which these rules organise can help to infer contextual meanings that can help to explain behaviours, attitudes, and preferences which is useful for devising PD strategies (Merceron & Yacef, 2010; Tondeur et al., 2021).

2. Problem statement

Best practices for designing effectivePD specifically for BL is well established, but how to address teaching staff's preferences for professionalisation in this context is not well known. This study takes a closer look at these technology acceptance profiles from the point of view of their PD preferences for implementing BL while using a new learning management system. Using data mining methods will uncover patterns and pathways that can reveal different behaviours within certain groups, and give indications for communicating, organising and targeting the different profiles according to their most likely needs and preferences. In sum, this study aims to answer the following research questions.

1. What are the professional development preferences of the groups with different technology acceptance levels?
2. What are the key relationships among these preferences within these groups?

3. Approach and methods

This study is situated within the context of the implementation of a new learning management system (LMS) and PD initiatives and projects surrounding the implementation in two Belgian higher education institutes. The LMS was first introduced in the year 2017 in the first institute and in 2018 in the second.

Clustering and profiling are useful methods for surveying a large population and breaking them down into smaller, more manageable groups (Milligan, 1980; Yim & Ramdeen, 2015). While clustering has its advantages, a disadvantage can be that smaller subpopulations can be overlooked in the process by forcing all participants into profiles (Hofmans et al., 2020). Decisions regarding the organisation and design of PD following the information based on such "hard" profiles is in danger of becoming "profile-centred", rather than person-centred. This being said, profiling users and potential participants according to their technology acceptance profiles is a useful first step towards understanding what their immediate general attitudes and needs are towards a certain technological innovation (Devolder et al., 2012). A previous study (AUTHORS 2019) explored how the present sample was clustered with the above-mentioned clustering methods, where participant and UTAUT factor characteristics are discussed and how these influence cluster membership.

3.1. Sample

Two institutes of higher education participated in this study, a university and a university of applied sciences. These two institutes were chosen as they had both implemented the same learning management system within the year preceding data collection. Participants who were involved in teaching were invited to take part in the survey. It was found that there was a significant overlap in types of teaching staff from both institutes that allowed for the merging of both samples. All participants agreed to an informed consent, which was approved by the university's data protection officer, and steps were taken by the principal researcher to guarantee the protection of the identities and email addresses of all participants. Personalised links were sent to all participating teaching staff, where they filled the survey out on Qualtrics, an online survey tool. The target population sample at the university included all appointed professors and researchers and guest professors, post-docs, Ph.D. researchers, teaching assistants and practical assistants, and other appointed pedagogical/teaching staff such as language teachers. The target population at the university of applied sciences was all staff with a teaching position or appointment. 349 teaching staff participated in the survey (249 from the university, and 100 from the university of applied sciences); only 217 participants, however, completed both the UTAUT and PD preferences sections of the survey.

3.2. Data collection

A survey consisting of two parts was constructed, the first a technology acceptance scale (UTAUT) and a self-constructed scale (PD preferences for BL). The items describing preferences for PD were based on possible scenarios described by Kennedy (2014) in her models of continuing PD framework. The PD preference items were formulated in the context of BL. 18 items were based on the transmissive, malleable and transformative models described in the framework.

21 UTAUT items were included that make up the core technology acceptance scales: Performance expectancy, effort expectancy, social influence, and facilitating conditions, along with other supporting scales: Attitude, anxiety, behavioural intention to innovate. Since the goal of this study is to understand how different groups of teaching staff want to professionalise themselves, the data is analysed on two levels: 1) Clustering and 2) Association rules analysis. The design of this research is illustrated in Fig. 3 below and is explained in further detail in the data collection and analysis sections.

All UTAUT items were formulated around the participants' experience and use of the new LMS while teaching or managing their courses. PD preference items were formulated according to several of the models of continuing PD described by Kennedy (2014), and inspired by the research of Czerniawsky et al. (2017). The item wording was centred around professionalisation for BL, meaning learning about, and how to implement BL in their future courses. BL was defined and explained prior to the section of questions to ensure that participants were aware of the pedagogical concepts and their application. The complete list of all survey items, including the adapted UTAUT items as well as the PD preference items can be found in Appendix A.

349 higher education teaching staff from two institutes in Belgium responded (faculty, lecturers as well as other staff) to an online survey. All respondents agreed to the informed consent prior to filing out the survey. Both institutes had implemented the same learning management system half a year to a year prior to administering the survey. All demographic information are detailed in Table 1 below.

3.3. Analysis

The data analysis was organised on two levels. On the first level, a two-step cluster analysis was used to find participant profiles. Previous studies have shown that the UTAUT scales are suitable for clustering, with the resulting profiles indicating various levels of technology acceptance (Devolder et al., 2012; Pynoo et al., 2011a). The first-level analyses were all carried out on SPSS (v.26). First, the individual scale scores were calculated for each individual participant, with missing values being deleted. The sample descriptives and scale statistics and reliability scores for each technology acceptance scale can be found in Table 1 below. Next, the four core UTAUT scales (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions) were selected as input variables for a hierarchical cluster analysis. Inspection of the agglomeration schedule, dendrogram and scree plot (all available in appendix B) revealed three viable clusters. Following these results, a K-means cluster determined into three groups was carried out using the same UTAUT scales as input variables. These resulted in three technology acceptance groups, high (above average scores), moderate (average scores), and low (below-average scores). A previous study by AUTHOR and colleagues (2019) also found three technology acceptance clusters in university teaching staff in a smaller sample within one institute. Cluster means of the entire sample can also be found in Table 2.

The second analysis level involved the association rules analysis of the PD preferences of each technology acceptance cluster. In order to facilitate analysis, the 7-point Likert scale responses were recoded at

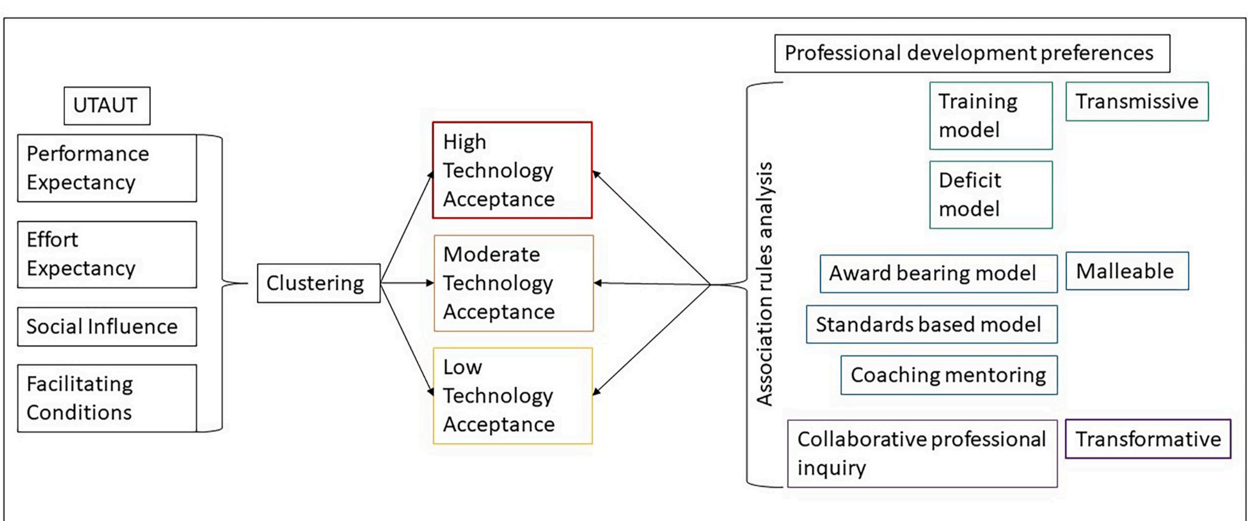


Fig. 3. Research design.

Table 1
Demographic information of the participants.

University (total N = 249)	N	University College (total N = 100)	N
Faculty	40	**Faculty**	12
Social sciences & solvay business	40	School of arts	10
school	35	Royal Conservatory	29
Medicine and pharmacy	33	Management, Media & Society	20
Engineering	13	Health & Landscape	9
Languages and Humanities	32	architecture	8
Pysical education and	14	Education	11
physiotherapy	38	Design & Technology	
Psychology and education	4	Vocational Programmes	
Law and Criminology			
Sciences and Bioengineering			
Missing			
Academic position	28	**Academic position**	90
Practical assistant	60	Lecturer	8
Assistant professor	40	Other	
Associate professor	14		
Full professor	12		
Full full professor	49		
Doctoral student	19		
Post -doc	7		
Pedagogical assistant	15		
Other	5		
Missing			
Followed pedagogical training	38	**Followed online platform**	69
Yes	21	**training**	4
Including training for blended	55	Yes	2
learning	46	No	75
No training	139	Not relevant	25
Not applicable	110	Total	
Total		Missing	
Missing			

Table 2
Technology Acceptance Scale descriptive statistics, reliability and cluster means.

	Clusters Clusters				
	1 1	2 2	3 3	Total means (SD) Total means (SD)	Crohnbach's alpha Crohnbach's alpha
N	108	128	45	281	
Performance expectancy scale	5.52	4.13	3.00	4.48 (1.22)	.837
Effort expectancy scale	5.77	4.92	2.81	4.91 (1.25)	.930
Social influence scale	5.88	4.80	4.41	5.15 (1.04)	.794
Facilitating conditions scale	5.39	4.17	3.52	4.53 (.98)	.773
Attitude scale	5.79	4.35	3.15	4.72 (1.28)	.913
Anxiety scale	1.86	2.49	2.93	2.32 (.97)	.788
Behavioural intention to innovate scale	4.88	3.90	3.15	4.16 (1.44)	.886

item-level into binary variables, with 4-1 (neutral - strongly disagree) as 0 and 5–7 (agree-strongly agree) as 1. The Apriori algorithm was used to analyse the associations among all 18 PD items (See Appendix A.2.). The analysis identifies item sets with the database which are understood as "rules" and consist of at least two items. Within a rule, one item will appear as the antecedent (A) and the other item as the consequent (C). This means that if item A with a specific value appears (in this case either 1 or 0), then highly probably item C with a specific value would also appear. These rules are expressed as: IF A, THEN C or represented graphically as A → C. The analysis was run with a lift cut-off of 2. Lift is an indication of the association strength between the items, thus the higher the lift, the more likely the association between the items. Setting a lift cut-off point results in showing the top number of rules above this value. Rules can be represented graphically using graph theory, which can be generated to visualize rule patterns (appendix C, Figs. 1–3).

4. Resultsfig1

A summary of the rules, averaged support, confidence, and lift from the three clusters can be seen in Table 3. The node distributions are summarised for each technology acceptance profile separately in the following sections. The high technology acceptance profile produced the highest number of rules with a collaborative professional inquiry item scoring highest in percentage distribution (how often an item occurs as part of a rule), while the moderate profile had the fewest rules and with a training model item scoring highest in percentage distribution, which was the same for the low profile as well.

Graphical patterns and heuristic interpretation of the rules.

An output graph was generated for each cluster, and these were analysed and simplified for the facilitation of discussion. All original graphs can be found in appendix C. The relationships between nodes are indicated by arrows. The antecedent is indicated by the arrow direction in such that A → C. If nodes are found in reciprocal relation to one another, this is indicated via bi-directional arrows ↔ between the nodes.

4.1. High technology acceptance profile rules

Participants with high technology acceptance appeared to have two distinct preference clusters, ten items in the preferred ("Agree") cluster and three items in the not preferred ("Disagree") cluster. Two items from each of the following models were contained in the Agree cluster: training model, deficit model, standards-based model, coaching-mentoring model and collaborative inquiry. The Disagree cluster contained two items from the awards-based model and one from the deficit model. The average confidence, support and lift values of each cluster are summarised in Table 4 below, and graphically represented below in Fig. 4. Each cluster is discussed in more detail below.

The high technology acceptance profile is characterized by an interest in BL (DM1 and DM3), and a desire for freedom and autonomy to professionalise themselves (DM1, CPIM2 and CPIM3), while at the same time they would like to combine this with coaching and guidance (CMM2 and CMM3). Clear guidelines and leadership from the institute with regards to BL implementation at the university seems to play an important role as well (SBM2 and SBM3). Furthermore, they do not see any value in award-bearing approaches, and are not motivated to professionalise themselves by an apparent lack of skills. These patterns are indicative of a group of participants that are interested in BL, motivated to professionalise themselves, while possibly actively taking part in the implementation process as well via transformative professional development approaches.

Table 3
Summary of rules extracted from the data sets of the three clusters.

	High	Moderate	Low
Dataset size	91	90	36
Total number of rules	64	37	55
Averaged support degree	.32	.32	.32
Averaged confidence degree	.86	.86	.87
Averaged lift	2.09	2.10	2.17
Top scoring item	CPIM3-1 (92 %)	TM1-1 (89 %)	TM1-1 (45 %)
Lowest scoring item	DM3-1 (25 %)	CMM2-1 (24 %)	CMM2-1 (9 %)

Table 4
High technology acceptance confidence, support, and lift.

	Confidence			Support			Lift		
	min	mean	max	min	mean	max	min	mean	max
Agree (62 rules)	0,72	0,86	1	0,30	0,32	0,37	2,00	2,09	2,23
Disagree (2 rules)	0,77	0,79	0,81	–	0,30	–	–	2,04	–

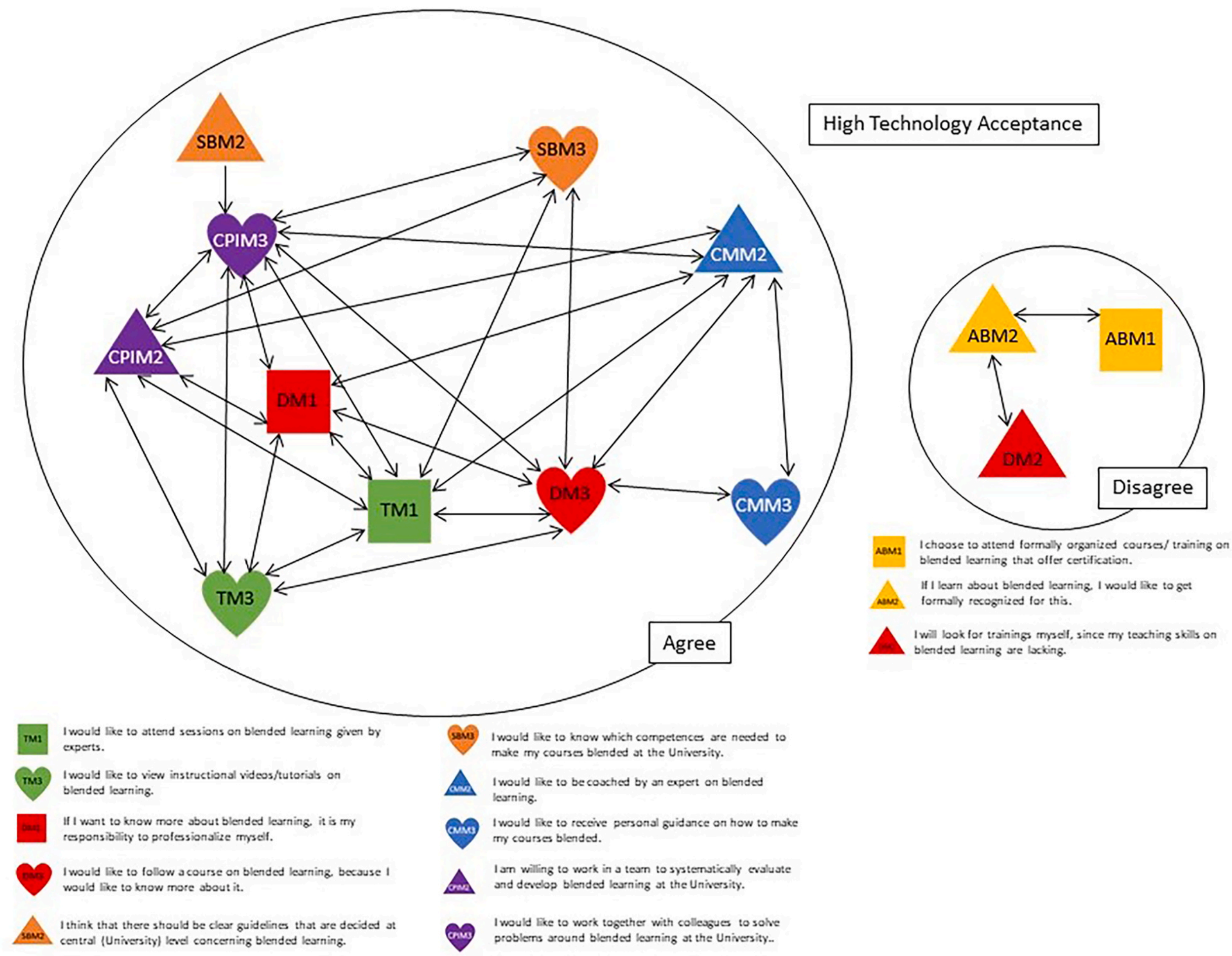


Fig. 4. Graphical representation of the rules for the high technology acceptance cluster.

4.2. Moderate technology acceptance profile rules

Participants with moderate technology acceptance appeared to have two distinct preference clusters, eight items in the preferred (“Agree”) cluster and three items in the not preferred (“Disagree”) cluster. Items from the following models were contained in the agree cluster: training model, deficit model, standards-based model, and the coaching-mentoring model. The disagree cluster contained one item from the awards-based model and two from the collaborative professional inquiry model. The average confidence, support and lift values of each cluster are summarised in Table 5 below, and graphically represented below in Fig. 5. Each cluster is discussed in more detail below.

The presence of, and strong connection between the training/deficit model items connected to coaching-mentoring and a standards-based item shows a strong preference for a structured and guided approach to professionalisation. This preference is further confirmed by the collaborative professional inquiry items being placed in the disagree cluster which further indicates a desire for less autonomy in favour of institutional guidance and leadership. They have little interest in transformative or award bearing approaches, instead the coaching and mentoring approaches play a central role in their preferences. The early majority, unlike the early adopters, do not prefer to be involved in

Table 5
Moderate technology acceptance confidence, support, and lift.

	Confidence			Support			Lift		
	min	mean	max	min	mean	max	min	mean	max
Agree (35 rules)	0,70	0,86	1	0,30	0,32	0,36	2	2,10	2,35
Disagree (2 rules)	0,76	0,83	0,89	–	0,32	–	–	2,13	–

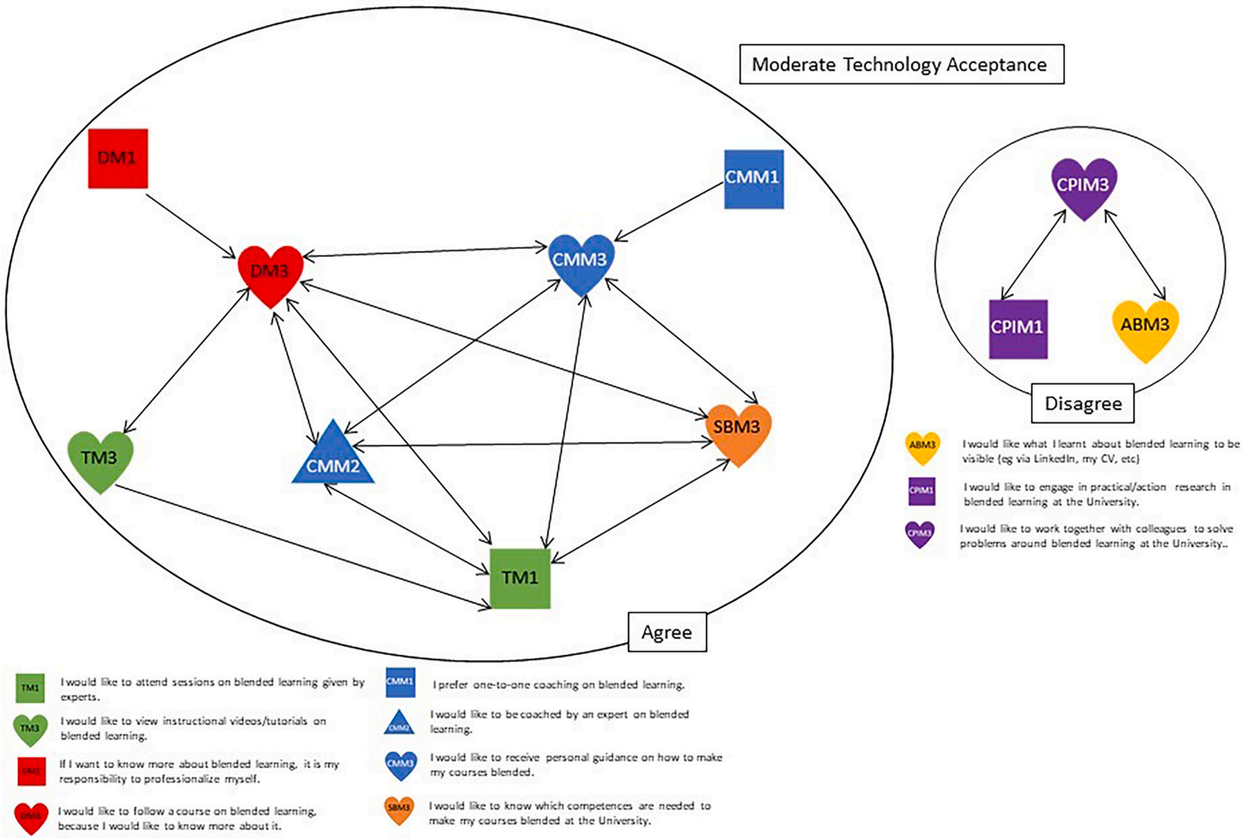


Fig. 5. Moderate technology acceptance preferences.

actively being part of the implementation process, instead they would like to be guided through the process and have the university take the lead for them.

4.3. Low technology acceptance profile

Participants with moderate technology acceptance appeared to have two distinct preference clusters, Ten items in the preferred ("Agree") cluster and fourteen items in the not preferred ("Disagree") cluster. Several items occurring with the agree cluster also occur within the disagree cluster, unlike in the high and moderate profiles in which different items appear within the agree and disagree clusters. Items from each of the following models were contained in the agree cluster: training model, deficit model, standards-based model, awards-based model, coaching-mentoring model and collaborative inquiry. The same model items were also contained in the disagree cluster. The average confidence, support and lift values of each cluster are summarised in Table 6 below, and graphically represented below in Fig. 6. Each cluster is discussed in more detail below.

4.4. Low technology acceptance profile: agree cluster patterns

Items that this group disagreed with were many instead. Almost all attributes included in the agree cluster are also in the disagree cluster, at the centre being the awards-based and community of practice approaches. Antecedent to the community of practice items are "follow a course because would like to know more" and "view instructional tutorials", indicating that simply following courses and accessing materials on BL will not motivate this group to start collaboratively working in a community of practice, no matter if accompanied by coaching or awards-based approaches. The reciprocal relationship between the "competences" items and the "follow a course" item in the disagree cluster shows that, in contrast to where these items are in relation with sessions given by experts, if the university were to merely approach professionalisation with a set of competences needed, this will likely not be enough to motivate the professors to seek out more information about BL.

It is important to note that with this group, the relationship sequences between the preferred items seems to be important, as the same items shown in relationship with different items or in a different sequence then become "disagree". The low technology acceptance group prefers, as with the moderates, also elements of a centrally guided initiative, however this is contingent on BL being perceived as relevant. Courses and sessions along with carefully planned personal guidance and coaching to complement these approaches can be offered to this group, along with clear guidelines and expectations from the institution.

Table 6
Low technology acceptance confidence, support, and lift.

	Confidence			Support			Lift		
	min	mean	max	min	mean	max	min	mean	max
Agree (33 rules)	0,74	0,88	1	0,30	0,33	0,37	2,02	2,17	2,71
Disagree (22 rules)	0,74	0,86	1	0,30	0,31	0,33	2,04	2,16	2,52

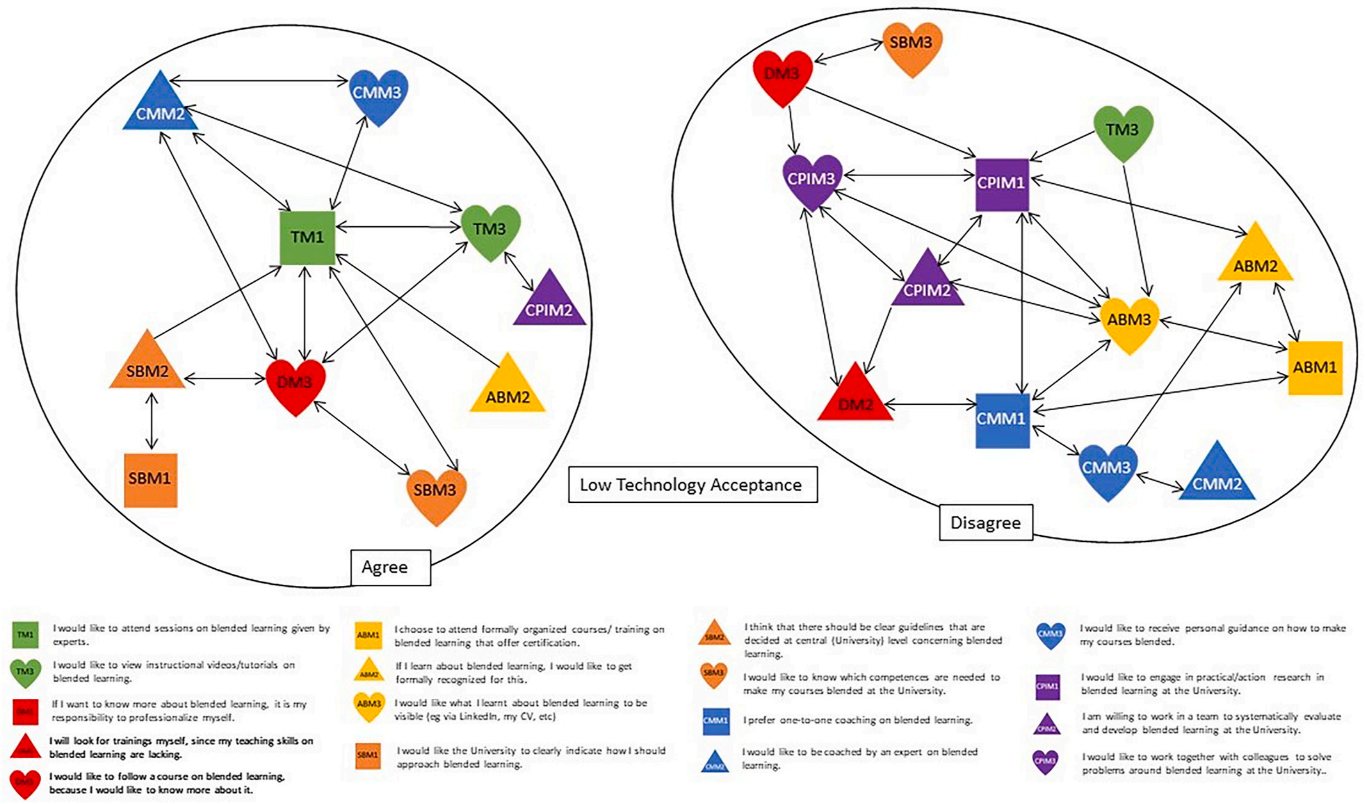


Fig. 6. Low technology acceptance preferences.

5. Discussion

The aim of this study was to understand how different groups of university teaching staff with various levels of technology acceptance want to be professionalized for BL. The results presented in this study show the professional development preferences for three groups: High, moderate and low technology acceptance. 18 preference items of professional development for BL were analysed per group. The rules analysis results for each group present with a unique number of rules, combinations and patterns of preferences.

Participants from the high technology acceptance profile indicated disagreement with award-bearing models, and at the same time an interest in BL. This is indicative of a group that is highly motivated to professionalise themselves without the need for external incentives. This group can be compared with the "high online-teaching readiness" group described by Scherer et al. (2021), meaning that this is a group of teachers that are likely already implementing BL in their teaching, and therefore recognize a value in further professional development initiatives.

The combination of these PD approaches, particularly the coaching mentoring models with the transmissive-transformative combination is in line with the findings from Zeggelaar (2020). They found that professional development initiatives are most effective when formative feedback moments, refresher courses are organised as a "reminder" for the participants to continue practicing the initiative (Zeggelaar et al., 2020). These results also align with the recent findings from Sherer and colleagues (2022) who found that teaching experience, and particularly online teaching experience, has a curvilinear relationship with online teaching readiness. This means that more experienced teachers are not necessarily more ready to teach online as a result of their experience. The authors therefore caution PD policy and decision makers not to dismiss the support needs of experienced teaching staff. Furthermore, the presence of the standards-based items within this profile's preferences confirms the importance of institutional leadership and vision in fostering transformation of teaching practices (Bohle Carbonell et al., 2013; Garrison et al., 2013).

The moderate technology acceptance group on the other hand seems to have a preference configuration that is between the high and the low. What is noticeable for this group, however, is the dislike of transformative approaches (collaborative inquiry) along with making what they learnt visible (awards-based). Unlike the other two groups, the moderates have a clear dislike for transformative, longitudinal approaches. Instead, the coaching mentoring approach is important for this group, which is an indication that they need more intensive guidance and follow up than the high technology acceptance group. This group can be compared to the "inconsistent online teaching readiness" group described by Scherer et al. (2021), in that likely these teachers feel the need for intensive institutional support because of their lacking readiness and uncertainty regarding BL. What is important to remember from the Kennedy (2014) framework is that the approaches that are found within the "malleable" section can be implemented in both a transmissive way or transformative way, depending on the context. Malleable approaches such as award-bearing models can be in the form of longitudinal courses that offer certification and further career paths, or a coaching/mentoring approach can help to transform practice if organised systematically with a clear vision (Desimone & Pak, 2017; Kennedy, 2014). The fact that coaching and mentoring are a part of the moderates' preferences should be a signal to PD designers that this is an approach that can and should be optimised in such a way that transformative change can still be reached (see Desimone & Pak, 2017), possibly by strengthening the existing support networks and teams (Gast et al., 2017), already situated in the context of these individuals.

These results show that guidance, coaching and central decision-making regarding BL from extrinsic factors are important when considering designing approaches for professionalisation towards BL for professors with moderate technology acceptance. From these results we also know that this group dislikes award bearing approaches ("making what I learnt visible") and collaborative inquiry ("willing to work in a team to systematically evaluate", and "practical/action research"), which may be an indication that the moderates might prefer spontaneous or informal professional development scenarios as well, since certification and recognition is not important for them (Kyndt et al., 2016). This is especially relevant in the post-pandemic higher education landscape, where PD supporters should consider embedding and fostering informal learning opportunities in online workspaces (Yu et al., 2021).

Noticeably, the low technology acceptance group, and what sets this group apart from the other two groups, is that the same items that are present in the agree cluster, were also present in the disagree cluster of rules. This group, therefore, prefers a certain order, or for certain conditions to be met, in order to consider the different approaches, and may be indicative of a certain pathway or sequence in which the approaches need to appear. The presence of the award-bearing item "want to receive formal recognition" (ABM2), indicates a need for an extrinsic incentive. Taking into account the role that social influence can play in this groups acceptance (AUTHORS), pressure from above can help with answering the "why are we doing this" question with clearly communicated decisions (Howard, 2013) and expectations from institutional decision makers (Garrison et al., 2013; Hulme & Winstone, 2017).

This group also scored highest in anxiety, which explains why many of the same items that appear in the agree cluster, also appear in the disagree cluster, which is indicative of a need for a closer inspection through qualitative analysis of this group to understand if there are subgroups within this group. Furthermore, these rules are indicative of the need for a "risk communication strategy" (e.g. Howard, 2013), or for promoting "psychological literacy" (eg. Hulme & Winstone, 2017), where continuous dialogue with these participants may be needed in order to consolidate and find the suitable matching professionalisation pathway that is relevant and meaningful for their personal and professional needs.

6. Implications for practice

What is clear is that the preferences for each group show a variety of approaches that can be adapted and aligned to the needs of the three groups. While the same items appear in all three groups, it is important to note that the items appear in different associations with one another. These results paint a possible scenario for professional development. Transmissive approaches such as workshops and seminars are a good start for promoting awareness by introducing the practical skills and knowledge needed, particularly regarding the technological tools needed for implementing BL (Kennedy, 2014, p. 694). Such workshops and seminars, however, should coincide with institutional leadership taking up the responsibility for establishing a vision and communicating the expected standards with regards to BL practice in the institutions (Garrison, 2013).

Further, sufficient resources need to be dedicated to setting up coaching and mentoring initiatives, which can either be formally or informally organised (Gast et al., 2017; Kyndt et al., 2016). The availability of these services need to be clearly communicated, particularly the low technology acceptance group needs to be targeted with carefully planned communication regarding the relevance and availability of support (Howard, 2013; Zeggelaar et al., 2020). Lastly, the transformative approaches, such as collaborative professional inquiry, are an important component for the high group, and possibly even for the low group. Transformation in teaching practices requires time and effort investment, and is usually a long term project or continuous process (Bohle Carbonell et al., 2013; Boylan et al., 2018; Vaughan, 2010). From the literature it can be inferred that this is an approach that can have an impact on addressing teacher beliefs (Teixeira Antunes et al., 2021) which has a profound effect on changing teaching practices (Deluca et al., 2015). Depending on the institutional context, such an initiative can be fostered from the bottom-up (Bohle Carbonell et al., 2013), or via formally organised groups steered by expert guidance (Garrison et al., 2013; Evans, 2014).

7. Limitations and future research

The professional development preference survey was developed based on the framework by Kennedy (2014). The items in this study were worded to reflect likely scenarios from various models and approaches as described by Kennedy (2005). However, some items need to be re-examined in future iterations of this survey, particularly those from the "deficit model". A further limitation to consider is response bias of the respondents that filled out the second half of the survey containing questions on how they wish to be trained. This might also explain why the low technology acceptance profile was also the smallest group of the three profiles.

Moreover, the results cannot simply be generalized to other educational contexts. Some themes were specifically connected to the context of universities. Also in other parts of the world, technology and professional development might be different in different parts of the world. Apart from the evaluation of professional development for BL outside the Flemish context, a crucial limitation of the present study concerns the quantitative nature of our study. Qualitative interviews or focus group sessions involving members from the three profiles can provide insights into why these groups have these preferences and how to best connect these with practical planning and professional development. Finally, this study is restricted to the perceptions of the respondents. Therefore, intervention studies are needed, also to grasp the dynamic nature of preparing teachers for BL. It would be interesting to verify whether and how university teachers profiles change according their needs and preferences.

8. Conclusion

This study aimed to understand how different groups of university teaching staff prefer to be professionalized. High technology acceptance was associated with a preference for innovative approaches which offer a high degree of autonomy. Moderate technology acceptance was associated with strong centrally organized institutional guidance and support. Low technology acceptance showed a complex pattern of associations indicative of a need for institutional guidance and support as well as clear incentives to professionalise. This analysis showed that technology acceptance can have an effect on preferences regarding professional development for BL. These findings can assist professional development organisers to understand how to approach their teaching staff with training and support offers that are better aligned with their needs and preferences.

CRediT authorship contribution statement

Anja Garone: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Sarah K. Howard:** Writing – review & editing, Methodology, Formal analysis. **Jie Yang:** Visualization, Resources, Methodology, Formal analysis. **Jo Tondeur:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Bram Pynoo:** Writing – review & editing, Supervision. **Bram Bruggeman:** Writing – review & editing. **Katrien Struyven:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Survey items and codes

Table A.1
UTAUT Survey Items

Codes	Item
Faculty	What is your (main) faculty affiliation?
Position	What is your academic position?
Performance Expectancy	
PE1	I would find Canvas useful within my teaching assignments.
PE2	The use of Canvas enables me to accomplish tasks quicker and more efficiently.
PE3	Using Canvas enhances my effectiveness as a teacher.
PE4	Through using Canvas, I increase my better chance for receiving good student feedback.
Effort Expectancy	
EE1	I find the interface of Canvas clear and understandable.
EE2	It is easy for me to become skillful at using Canvas.
EE3	I find Canvas easy to use.
EE4	Learning to work with Canvas is easy.
Social Influence	
SI1	My colleagues think that I should use Canvas more innovatively.
SI2	Colleagues, who are important to me, think that I should use Canvas.
SI3	The educational council of my programme supports the use of Canvas.
SI4	In general, the university supports the use of Canvas.
SI5	In general, the faculty supports the use of Canvas.
SI6	The chairman of my educational council thinks that I should use Canvas.
Facilitating conditions	
FC1	I have the resources necessary to use Canvas.
FC2	Canvas is compatible with the way I teach.
FC3	A specific person is available for assistance with difficulties when using Canvas.
FC4	I have the knowledge necessary to use Canvas.
FC5	I feel that I can make informed decisions about which tools/resources to use within Canvas.
FC6	I feel that I can fully take advantage of Canvas thanks to the resources within Canvas.
FC7	I have looked for tools outside of Canvas so that I can further innovate with my teaching through technology.
Attitude	
ATT1	The use of Canvas at our university is a good idea.
ATT2	Canvas makes teaching more interesting.
ATT3	Working with Canvas is fun.
ATT4	I enjoy using Canvas.
ATT5	Canvas makes learning more interesting for the students.
Anxiety	
ANX1	I feel apprehensive about using Canvas.
ANX2	It scares me to think that I could unintentionally lose information if I use Canvas.
ANX3	I fear that the information that I post online on Canvas could be misused.
ANX4	I fear that the information that I post online on Canvas can be misinterpreted.
ANX5	I hesitate to use Canvas for fear of making mistakes I cannot correct.
ANX6	The use of Canvas intimidates me.
Intensity of Use	
IU	To what extent do you use Canvas? (Least = 1 – Most = 7)
Frequency	
FREQ	How often do you use Canvas?
Voluntariness of Use	
VOL	I experience the use of Canvas (Voluntary = 1 – Compulsory = 7)
Behavioural intention to innovate	
BII1	I intend to approach my following course more innovatively.
BII2	Because of the possibilities that Canvas offers, I plan to approach my next course more innovatively.
BII3	I predict that I would approach my next course more innovatively, because of the possibilities offered by Canvas.

Table A.2
Scales based on Models of professional development (Kennedy, 2014)

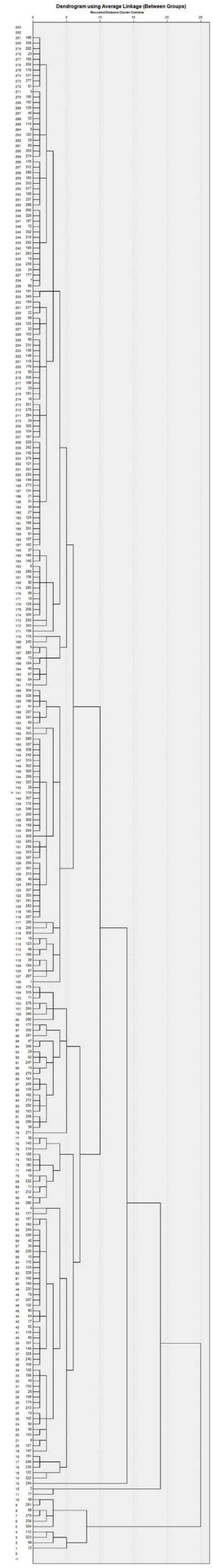
Purpose of Model	Model	Code	Translation (not validated)
Transmissive	Training model	TM1	I would like to attend sessions on blended learning given by experts.
		TM2	I would like to independently develop my teaching competences by accessing information about blended learning (eg. Online, reading a book, etc).
		TM3	I would like to view instructional videos/tutorials on blended learning.
	Deficit model	DM1	If I want to know more about blended learning, it is my responsibility to professionalise myself.
		DM2	I will look for trainings myself, since my teaching skills on blended learning are lacking.
		DM3	I would like to follow a course on blended learning, because I would like to know more about it.

(*continued on next page*)

Table A.2 (*continued*)

Purpose of Model	Model	Code	Translation (not validated)
Malleable	Award bearing model	ABM1	I choose to attend formally organised courses/training on blended learning that offer certification.
		ABM2	If I learn about blended learning, I would like to get formally recognized for this.
		ABM3	I would like what I learnt about blended learning to be visible (eg via LinkedIn, my CV, etc)
	Standards based model	SBM1	I would like the University to clearly indicate how I should approach blended learning.
		SBM2	I think that there should be clear guidelines that are decided at central (University) level concerning blended learning.
		SBM3	I would like to know which competences are needed to make my courses blended at the University.
	Coaching-mentoring model	CMM1	I prefer one-to-one coaching on blended learning.
		CMM2	I would like to be coached by an expert on blended learning.
		CMM3	I would like to receive personal guidance on how to make my courses blended.
Transformative	Collaborative professional inquiry	CPIM2	I am willing to work in a team to systematically evaluate and develop blended learning at the University.
		CPIM3	I would like to work together with colleagues to solve problems around blended learning at the University.
		CPIM1	I would like to engage in practical/action research in blended learning at the University.

Appendix B. Dendrogram for combined sample hierarchical cluster analysis


Dendrogram using Average Linkage (Between Groups)
Rescaled Distance Cluster Combine
0
5
10
15
20
25

Appendix C. Original Association Rules and Graphs

Table C.1
Item node distribution per cluster

Cluster 1				Cluster 2				Cluster 3			
Item	A	C	Total	Item	A	C	Total	Item	A	C	Total
CMM2-1	.22	.17	.39	CMM1-1	.03	.0	.03	CMM2-1	.13	.09	.22
SBM2-1	.06	.0	.06	DM3-1	.46	.41	.86	CMM3-1	.05	.04	.09
TM1-1	.38	.25	.63	TM1-1	.46	.43	.89	SBM1-1	.02	.02	.04
CMM3-1	.03	.02	.05	SBM3-1	.24	.19	.43	SBM2-1	.07	.04	.11
CPIM3-1	.33	.59	.92	CPIM3-0	.03	.03	.05	DM3-1	.2	.12	.35
CPIM2-1	.5	.28	.78	CPIM1-0	.03	.03	.05	SBM3-1	.07	.07	.15
DM3-1	.38	.27	.64	ABM3-0	.03	.03	.05	ABM2-1	.02	.0	.02
ABM2-0	.02	.02	.03	CMM3-1	.3	.22	.51	CPIM2-1	.02	.02	.04
DM2 -0	.02	.02	.03	DM1-1	.03	.0	.03	TM3-1	.09	.05	.15
ABM1-0	.02	.02	.03	TM3-1	.05	.03	.08	SBM3-0	.02	.02	.04
TM3-1	.14	.06	.2	CMM2-1	.24	.24	.49	DM3-0	.04	.02	.05
DM1-1	.13	.08	.2					TM1-1	.18	.27	.45
SBM3-1	.08	.05	.13					CMM3-0	.07	.05	.13
								CMM2-0	.02	.02	.04
								CMM1-0	.07	.05	.13
								CPIM1-0	.09	.15	.24
								ABM1-0	.05	.04	.09
								ABM3-0	.09	.13	.22
								TM3-0	.02	.0	.02
								CPIM3-0	.07	.07	.15
								CPIM2-0	.07	.04	.11
								DM2-0	.04	.04	.07
								ABM2-0	.02	.04	.05

A = Antecedent, C = Consequency
1 = Agree, 0 = Disagree.

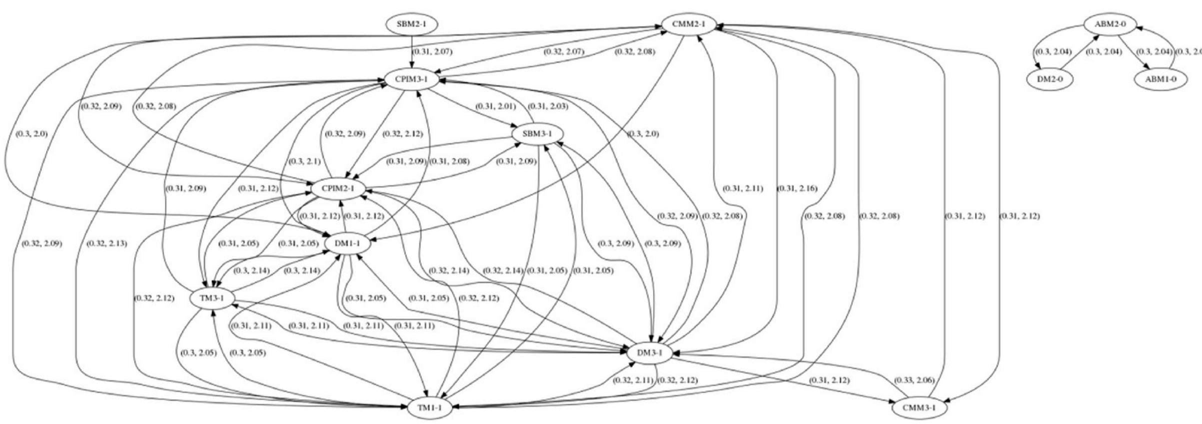


Fig. C.1. Original directed graph output from the association rules analysis for the high technology acceptance group

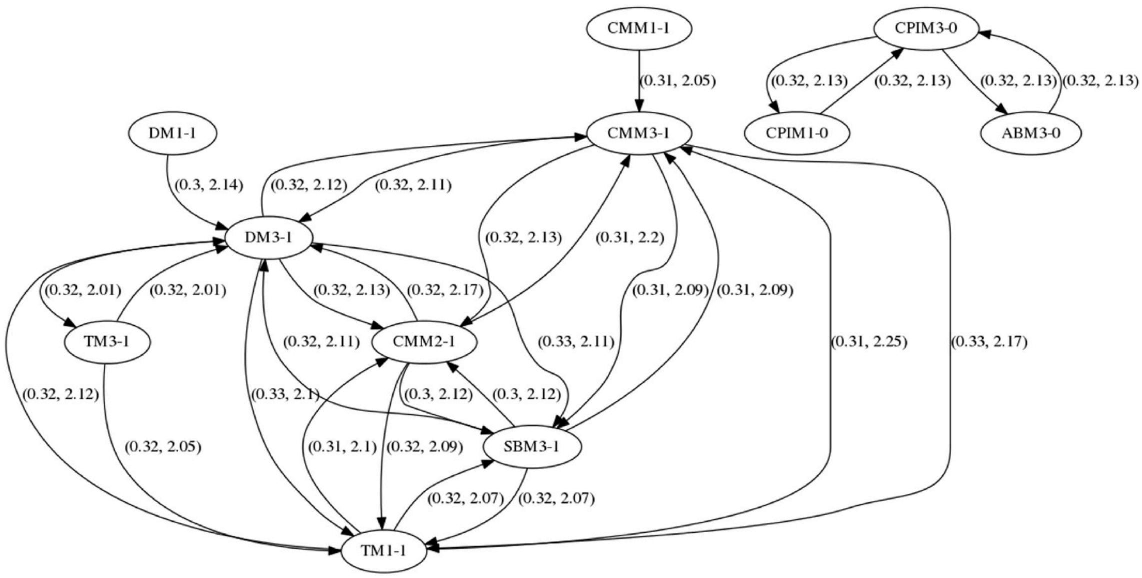


Fig. C.2. Original directed graph output from the association rules analysis for the moderate technology acceptance group

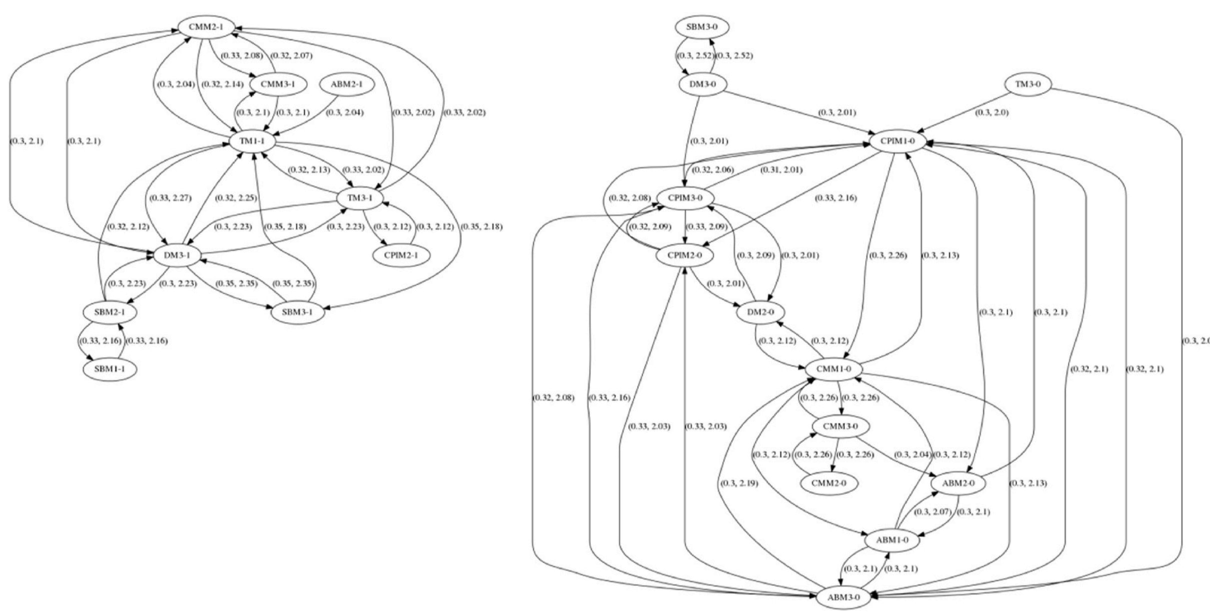


Fig. C.3. Original directed graph output from the association rules analysis for the low technology acceptance group

Data availability

Data will be made available on request.

References

Baker, R. S. J. D. (2010). Data mining for education. *International encyclopedia of education, 7*(3), 112–118.

Bingimlas, K. A. (2009). Barriers to the successful integration of ict in teaching and learning environments: A review of the literature. *Eurasia Journal of Mathematics, Science and Technology Education, 5*(3), 235–245.

Boelens, R., Voet, M., & De Wever, B. (2018). The design of blended learning in response to student diversity in higher education: Instructors' views and use of differentiated instruction in blended learning. *Computers & Education, 120*, 197–212.

Bohle Carbonell, K., Dailey-Hebert, A., & Gijselaers, W. (2013). Unleashing the creative potential of faculty to create blended learning. *The Internet and Higher Education, 18*, 29–37.

Boylan, M., Coldwell, M., Maxwell, B., & Jordan, J. (2018). Rethinking models of professional learning as tools: A conceptual analysis to inform research and practice. *Professional Development in Education, 44*(1), 120–139.

Czerniawski, G., Guberman, A., & MacPhail, A. (2017). The professional developmental needs of higher education-based teacher educators: An international comparative needs analysis. *European Journal of Teacher Education, 40*(1), 127–140.

DeLuca, C., Shulha, J., Luhanga, U., Shulha, L. M., Christou, T. M., & Klinger, D. A. (2015). Collaborative inquiry as a professional learning structure for educators: A scoping review. *Professional Development in Education, 41*(4), 640–670.

Desimone, L. M. (2009). Improving impact studies of teachers' professional development: Toward better conceptualizations and measures. *Educational Researcher, 38*(3), 181–199.

Desimone, L. M., & Pak, K. (2017). Instructional coaching as high-quality professional development. *Theory into practice, 56*(1), 3–12.

Devolder, P., Pynoo, B., Sijnave, B., Voet, T., & Duyck, P. (2012). Framework for user acceptance: Clustering for fine-grained results. *Information & Management, 49*(5), 233–239.

Dias, S. B., & Diniz, J. A. (2012). Blended learning in higher education: Different needs, different profiles. *Procedia Computer Science, 14*, 438–446.

Díaz, M. J. F., Santaolalla, R. C., & González, A. G. (2010). Faculty attitudes and training needs to respond the new European Higher Education challenges. *Higher Education, 60*(1), 101–118.

Ding, A. C. E., Ottenbreit-Leftwich, A., Lu, Y. H., & Glazewski, K. (2019). EFL teachers' pedagogical beliefs and practices with regard to using technology. *Journal of Digital Learning in Teacher Education, 35*(1), 20–39.

Dysart, S., & Weckerle, C. (2015). Professional development in higher education: A model for meaningful technology integration. *Journal of Information Technology Education: Innovations in Practice, 14*(1), 255–265.

Ertmer, P. A. (1999). Addressing first-and second-order barriers to change: Strategies for technology integration. *Educational Technology Research & Development, 47*(4), 47–61.

Evans, L. (2014). Leadership for professional development and learning: Enhancing our understanding of how teachers develop. *Cambridge Journal of Education, 44*(2), 179–198.

Fraser, C., Kennedy, A., Reid, L., & Mckinney, S. (2007). Teachers' continuing professional development: Contested concepts, understandings and models. *Journal of In-Service Education, 33*(2), 153–169.

Garrison, D. R., & Kanuka, H. (2004). Blended learning: Uncovering its transformative potential in higher education. *The internet and higher education, 7*(2), 95–105.

Garrison, D. R., & Vaughan, N. D. (2013). Institutional change and leadership associated with blended learning innovation: Two case studies. *The internet and higher education, 18*, 24–28.

Gast, I., Schildkamp, K., & van der Veen, J. T. (2017). Team-based professional development interventions in higher education: A systematic review. *Review of Educational Research, 87*(4), 736–767.

Guskey, T. R. (2000). *Evaluating professional development*. Corwin press.

Guskey, T. R. (2002). Does it make a difference? Evaluating professional development. *Educational Leadership, 59*(6), 45.

Hall, G., & Hord, S. (1987). *Change in schools: Facilitating the process*. Albany, NY: SUNY Press.

Hofmans, J., Wille, B., & Schreurs, B. (2020). Person-centered methods in vocational research. *Journal of Vocational Behavior, 118*, Article 103398. https://doi.org/10.1016/j.jvb.2020.103398

Howard, S. K. (2013). Risk-aversion: Understanding teachers' resistance to technology integration. *Technology, Pedagogy and Education, 22*(3), 357–372.

Howard, S. K., Ma, J., & Yang, J. (2016). Student rules: Exploring patterns of students' computer-efficacy and engagement with digital technologies in learning. *Computers & Education, 101*, 29–42.

Howard, S. K., Tondeur, J., Ma, J., & Yang, J. (2021). What to teach? Strategies for developing digital competency in preservice teacher training. *Computers & Education, 165*, Article 104149.

Hulme, J. A., & Winstone, N. E. (2017). Do no harm: Risk aversion versus risk management in the context of pedagogic frailty. *Knowledge Management & E-Learning: International Journal, 9*(3), 261–274.

Iesalc, U. N. E. S. C. O. (2020). *Covid-19 and higher education: Today and tomorrow. impact analysis, policy responses and recommendations*. UNESCO. tech. rep.

Kennedy, A. (2005). Models of continuing professional development: A framework for analysis. *Journal of In-Service Education, 31*(2), 235–250.

Kennedy, A. (2014). Understanding continuing professional development: The need for theory to impact on policy and practice. *Professional Development in Education, 40*(5), 688–697.

Kyndt, E., Gijbels, D., Grosemans, I., & Donche, V. (2016). Teachers' everyday professional development: Mapping informal learning activities, antecedents, and learning outcomes. *Review of Educational Research, 86*(4), 1111–1150.

Merceron, A., Blikstein, P., & Siemens, G. (2015). Learning analytics: From big data to meaningful data. *Journal of Learning Analytics, 2*(3), 4–8.

Merceron, A., & Yacef, K. (2010). Measuring correlation of strong symmetric association rules in educational data. In C. Romero, S. Ventura, M. Pechenizkiy, & R. S. J. D. Baker (Eds.), *Handbook of educational data mining* (pp. 245–255). Taylor & Francis Group.

Merchie, E., Tuytens, M., Devos, G., & Vanderlinde, R. (2018). Evaluating teachers' professional development initiatives: Towards an extended evaluative framework. *Research Papers in Education, 33*(2), 143–168.

Milligan, G. W. (1980). An examination of the effect of six types of error perturbation on fifteen clustering algorithms. *Psychometrika, 45*(3), 325–342.

Morin, A. J., Bujacz, A., & Gagné, M. (2018). *Person-centered methodologies in the organizational sciences: Introduction to the feature topic*.

Pérez-Foguet, A., Lazzarini, B., Giné, R., Velo, E., Boni, A., Sierra, M., Zolezzi, G., & Trimingham, R. (2018). Promoting sustainable human development in engineering: Assessment of online courses within continuing professional development strategies. *Journal of Cleaner Production, 172*, 4286–4302.

Philipsen, B., Tondeur, J., Roblin, N. P., Vanslambrouck, S., & Zhu, C. (2019). Improving teacher professional development for online and blended learning: A systematic meta-aggregative review. *Educational Technology Research & Development, 67*(5), 1145–1174.

Pynoo, B., Devolder, P., Tondeur, J., Van Braak, J., Duyck, W., & Duyck, P. (2011a). Predicting secondary school teachers' acceptance and use of a digital learning environment: A cross-sectional study. *Computers in Human Behavior, 27*(1), 568–575.

Rogers, E. (2003). *Diffusion of innovations* (5th ed.). New York, NY: Simon and Schuster. ISBN 978-0-7432-5823-4.

Scherer, R., Howard, S. K., Tondeur, J., & Siddiq, F. (2021). Profiling teachers' readiness for online teaching and learning in higher education: Who's ready? *Computers in Human Behavior, 118*, Article 106675.

Schoonenboom, J. (2014). Using an adapted, task-level technology acceptance model to explain why instructors in higher education intend to use some learning management system tools more than others. *Computers & Education, 71*, 247–256.

Siemens, G., Gašević, D., & Dawson, S. (2015). Preparing for the digital university: A review of the history and current state of distance, blended, and online learning. Retrieved November 21st, 2021 https://researchmgt.monash.edu/ws/portalfiles/portal/256525723/256524746_oa.pdf.

Surry, D. W., Ensminger, D. C., & Haab, M. (2005). A model for integrating instructional technology into higher education. *British journal of educational technology, 36*(2), 327–329.

Swaffield, S. (2014). Models of professional learning and the global imperative of professional development in education. *Professional Development in Education, 40*(3), 331–335.

Teixeira Antunes, V., Armellini, A., & Howe, R. (2021). Beliefs and engagement in an institution-wide pedagogic shift. *Teaching in Higher Education*, 1–21.

Tondeur, J., Howard, S. K., & Yang, J. (2021). One-size does not fit all: Towards an adaptive model to develop preservice teachers' digital competencies. *Computers in Human Behavior, 116*, Article 106659.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425–478.

Villani, D., Morganti, L., Carissoli, C., Gatti, E., Bonanomi, A., Cacciamani, S., … Riva, G. (2018). Students' acceptance of tablet PCs in Italian high schools: Profiles and differences. *British Journal of Educational Technology, 49*(3), 533–544.

Weiss, H. M., & Rupp, D. E. (2011). Experiencing work: An essay on a person-centric work psychology. *Industrial and Organizational Psychology, 4*(1), 83–97.

Wilfong, J. D. (2006). Computer anxiety and anger: The impact of computer use, computer experience, and self-efficacy beliefs. *Computers in Human Behavior, 22*(6), 1001–1011.

Yim, O., & Ramdeen, K. T. (2015). Hierarchical cluster analysis: Comparison of three linkage measures and application to psychological data. *The quantitative methods for psychology, 11*(1), 8–21.

Yu, H., Zhang, J., & Zou, R. (2021). A Motivational mechanism framework for teachers' online informal learning and innovation during the COVID-19 pandemic. *Frontiers in Psychology, 12*, Article 601200.

Zawacki-Richter, O. (2021). The current state and impact of Covid-19 on digital higher education in Germany. *Human Behavior and Emerging Technologies, 3*(1), 218–226.

Zeggelaar, A., Vermeulen, M., & Jochems, W. (2020). Evaluating effective professional development. *Professional Development in Education*, 1–21.