Received 11 January 2021
Revised 4 July 2021
19 September 2021
Accepted 21 September 2021

What makes volunteer mentors tick? A case study in a preparatory online training course

Analia Cicchinelli and Viktoria Pammer-Schindler
Data-Driven Business, Know-Center GmbH, Graz, Austria and
Institute of Interactive Systems and Data Science, Graz University of Technology, Graz, Austria

Abstract

Purpose – This paper aims to understand what drives people – their motivations, autonomous learning attitudes and learning interests – to volunteer as mentors for a program that helps families to ideate technological solutions to community problems.

Design/methodology/approach – A three-phase method was used to build volunteer mentor profiles; elicit topics of interest and establish relationships between those. The mentor profiles were based on self-assessments of motivation, attitude toward lifelong learning and self-regulated learning strategies. The topics of interest were elicited through content analysis of answers to reflection questions. Statistical methods were applied to analyze the relationship between the interests and the mentor profiles.

Findings – Bottom-up clustering led to the identification of three mentor groups (G1 "low"; G2 "high" and G3 "medium") based on pre-survey data. While content analysis led to identifying topics of interest: communication skills; learning AI; mentoring; prototype development; problem-solving skills; working with families. Analyzing relationships between mentor profile and the topics of interest, the group G3 "medium," with strong intrinsic motivation, showed significantly more interest in working with families. The group with the overall highest scores (G2 "high") evidenced also substantial interest in learning about AI, but with high variability between members of the group.

Originality/value – The study established different types of learning interests of volunteer mentors and related them to the mentor profiles based on motivation, self-regulated learning strategies and attitudes toward lifelong learning. Such knowledge can help organizations shape the volunteering experience to provide more value to volunteers. Furthermore, the reflection questions can be used by volunteers as an instrument for reflection and by organizations to elicit the learning interests of volunteers.

Keywords Motivation, Self-regulated learning strategies, Lifelong learning, Reflection, Mentoring, Professionals, Nonprofit organization, Volunteer mentors

Paper type Research paper

This work was funded partially by Technovation and partially within the Austrian COMET Program – Competence Centers for Excellent Technologies – under the auspices of the Austrian Federal Ministry of Transport, Innovation and Technology, the Austrian Federal Ministry of Economy, Family and Youth and by the State of Styria. COMET is managed by the Austrian Research Promotion Agency FFG.+.

1. Introduction

The present study is set in the context of an artificial intelligence (AI) Family Challenge, an AI and entrepreneurial skills training program for disadvantaged families carried out by a nonprofit organization. The families are guided by volunteer mentors in the development of a project using AI. The mentors (professionals) receive training (not mandatory) on mentoring, the challenge and core concepts of AI. The mentor training consists of face-2-face training and training through an online platform. In this work, we study those mentors that participated in the online training in autumn 2019.

The mentor training in the online platform holds similarities to courses in massive opne online course (MOOCs) with educational context, in that there is a platform offering learning contents organized in modules. In Massive Opne Online Course contexts, a course is typically completed after some form of assessment (of at least the engagement, but typically of the knowledge and competence). In the context of this study, even more, important than course completion is the subsequent commitment to and completion of mentorship of a family throughout the challenge.

In the educational context, professionals are highly motivated to learn when the learning aligns with their needs and their values associated with their professional career; or to obtain certification (Littlejohn *et al.*, 2012, 2016). However, as prospective volunteer mentors who start the mentor training are not looking for certification (which was not offered), their motivation must be rooted in their needs and values.

One of the main concerns faced by the organization is to increase the number of volunteers and retain them in the program from training to mentoring. According to the literature, careful attention to matching affordances and opportunities to goals and motives seems necessary for successful recruitment, placement and retention of mentors (Stukas and Tanti, 2005). Taking that into account, we present a methodology that: measures motivation, self-regulated skills and attitude toward continuous learning as a mentor profile, extract the learning interests of mentors and links those interests to the mentor profile.

With regard to that, the study details different types of learning interests of volunteer mentors and relates them to their profiles in terms of motivation, self-regulated learning strategies and attitudes toward lifelong learning. Identifying the relationship between the mentor groups and the interests allows the organization to adapt the training according to the mentor's motivations and interests. This methodology, in particular the reflection questions, can be further used as an instrument of eliciting interests and offering direct value to volunteers and learners, who by means of reflection become aware of learning something new through volunteering and the potential impact that it may have on their own private life or work.

The outline of the paper is as follows: Section 2 presents a background, the main concepts and related works. Section 3 presents the research questions that guide our study. Section 4 presents the methods and research instruments. Section 5 describes the analysis and results. Finally, Section 6 contains a discussion and conclusions.

2. Background and related work

2.1 Mentoring and volunteering

Mentors are typically defined as individuals with advanced experience and knowledge who are committed to providing support to and increasing the career advancement of junior organizational members, their protégés (Allen, 2003). Mentoring programs can be found in various domains: business organizations as a response to the need to support employees in their efforts to improve themselves and achieve the company's goals (Bortnowska and Seiler, 2019), educational settings where a more experienced student guides the less experienced through a new academic environment (Voyles *et al.*, 2011) and in nonprofit organizations (non-governmental, social, third-sector). In the latter, as the spectrum of mentors is broader than in the other sectors, it can be applied to more categories of employees, i.e. not only to managers and paid employees but also to social workers and volunteers (Bortnowska and Seiler, 2019). This is particularly relevant to our case, where volunteer mentors take part in a nonprofit program to support families in a technology-oriented project.

Volunteering is any activity in which time is given freely to benefit another person, group or organization (Wilson, 2000). Many researchers investigated and assessed the motivations of volunteers (Clary *et al.*, 1998; Clary and Snyder, 1999; Snyder *et al.*, 2000; Allison *et al.*, 2002). The "volunteer motivations model" emphasizes individuals' motivations for or goals in volunteering. Research indicates that people give service for a variety of reasons, e.g. to learn new skills, to develop themselves, to enhance self-esteem, to prepare for a career, to express personal values and community commitment and even to reduce ego conflicts or identity threats (Thoits and Hewitt, 2001).

Regarding mentoring, several studies assessed the motives that underlie mentoring behavior through different instruments: self-assessment or interview (Allen *et al.*, 1997; Allen, 2003; Allen and Eby, 2003; Janssen *et al.*, 2014). The results focus on self-enhancement, intrinsic satisfaction and benefit to the organization and others, representing life and career stages. In the specific context of mentoring in nonprofit organizations (i.e. the context of our study), in their literature review, Bortnowska and Seiler (2019) cited a small number of reviewed mentoring publications and indicated that this area of knowledge is only beginning to shape. Through quantitative and qualitative analysis a few works analyzed issues related to the influence of mentoring on the functioning of nonprofit organizations (Bogdanova, 2008; Momoh *et al.*, 2015; Nyamori, 2015; Smith *et al.*, 2005; Washington, 2011, ref. to these studies in Bortnowska and Seiler, 2019). However, to date, no studies related to motivation have been found.

In our work, volunteer mentors in a nonprofit organization receive training on diverse topics through an online platform. This means that before developing their activity as mentors, they are professionals who are trained in the role of learners. Taking this into account, we consider it relevant to assess:

- the motivation (intrinsic and extrinsic motivation) and self-efficacy related to learning on the online platform and related to the mentoring;
- self-regulated skills; and
- attitude toward lifelong learning.

The latter are also relevant factors for our research because one of the objectives of the program in which our participants are enrolled is to encourage and promote goal setting, ideation and continuous learning in the mentees.

2.2 Motivation

Motivation is reflected in the choice of courses of action and in the intensity and persistence of effort (Bandura, 1994). To be motivated means to be moved to do something (Ryan and Deci, 2000). Two types of motivation are often distinguished based on different reasons or goals that give rise to an action: intrinsic motivation (which refers to doing something because it is inherently interesting or enjoyable) and extrinsic motivation (which refers to doing something because it leads to a separable outcome) (Ryan and Deci, 2000). In this way, intrinsic motivation refers to doing an activity for the enjoyment and inherent satisfaction of performing a task, while extrinsic motivation relates to external values and demands and refers to doing an activity for the usefulness or task value (Alario-Hoyos *et al.*, 2017), such as career benefit. In regard to volunteerism, Finkelstein (2009) ascribed 6 functions to motives: 5 internal ones (i.e. values, understanding, social, enhancement and protective functions) and 1 external one (i.e. the career function). Accordingly, in our study, extrinsic motivation refers to the motivation arising from the expectation of a tangible benefit in professional life and is referred to as career motivation, as in Glynn *et al.* (2011).

A component that plays an important role in motivation is self-efficacy, which refers to people's beliefs about their capabilities to produce effects: people form beliefs about what they can do and the possible outcomes of their actions (Bandura, 1994). Self-beliefs of efficacy determine the goals people set for themselves, how much effort they expend, how long they persevere in the face of difficulties and their resilience to failures (Bandura, 1994). This metacognitive capability to reflect upon oneself and the adequacy of one's thoughts and actions influences the selection of appropriate strategies for achieving goals and one's own self-regulatory skills.

2.3 Self-regulation and attitude toward lifelong learning

Self-regulatory strategies are described as "self-generated thoughts, feelings and actions that are planned and cyclically adapted to the attainment of personal goals" (Zimmerman, 2000). These strategies refer to self-control, self-reflection and self-evaluation about a particular task and its impact in the personal and professional domain (Littlejohn *et al.*, 2016). A self-regulated learner is an autonomous learner that is able to set goals, apply appropriate knowledge and skills, engage in self-direction and self-evaluation, locate required information and adapt her/his learning strategies to different conditions (Kirby *et al.*, 2010). This self-directed learning refers to a permanent attitude toward learning or, in other words, the attitude toward lifelong learning. The latter is defined as:

> A continuously supportive process, which stimulates and empowers individuals to acquire all the knowledge, values, skills and understanding they will require throughout their lifetimes and apply them with confidence, creativity and enjoyment in all roles, circumstances and environments (Collins, 2004).

Lifelong learners are critical and creative thinkers, problem solvers and decision-makers and they need to practice regular self-reflection. These competencies are recognized as some of the most important goals in education applicable to one's profession and all aspects of one's life (Collins, 2004).

2.4 Participation and learning in online environments

In the context of our work, volunteer mentors received training in diverse topics through an online platform, that was similar to MOOC. In that regard, we investigated studies of learning via online platforms that assess motivation and learning skills. An ample body of research has been dedicated to how motivation and learning strategies related to the learner's behavior. Alario-Hoyos *et al.* (2017) demonstrated that the learner's motivation and self-regulated learning strategies are important for understanding the behavior of MOOC learners. Kizilcec and Schneider (2015) emphasized that motivation provides a lens for understanding online learners and designing online courses, which allow better support of their needs. Various authors analyzed the interactions of learners with online learning environments to detect the learning strategies that they apply Littlejohn *et al.* (2016), Kizilcec *et al.* (2017), Pardo *et al.* (2016) and Cicchinelli *et al.* (2018) or the patterns in the student's behavior that are indicative of the adopted learning strategies (Jovanović *et al.*, 2017).

Specifically, in the context of workplace learning, Margaryan *et al.* (2009) examined how professionals self-regulate their learning in MOOCs, as autonomy and self-regulation have been recognized as core components of expert performance. Our study differs in that we did not seek to relate these dimensions to performance during training. Rather, we assessed these dimensions to build a mentor profile and advanced beyond these factors by eliciting and analyzing topics of interest for mentors. Thus, our goal was to determine which interests emerge during the mentor's training that guides the volunteer's mentoring and to establish the connection with the mentor's profile.

In this work, we targeted volunteer mentors and studied their interests from the perspective of motivation, lifelong learning attitude and self-regulation strategies. Our work differs from the previous research in that it focuses on topics of interest as they arise during the mentor training and makes mentors aware of their relationship to professional and personal life. We take advantage of the online platform in the mentor training program to pose the reflection questions that serve as a vehicle for studying the topics that are interesting and enjoyable to mentors.

3. Research questions

Considering that the goals of this study are to assess motivation, attitude toward lifelong learning and self-regulation to create a mentor's profile; define the topics of interest (extracted from the reflection questions) in the mentor training and establish possible relationships between the topics of interest and the mentors' profiles, we formulated the following research questions:

RQ1. What characterizes our study's participants in terms of attitude toward lifelong learning, motivation and self-regulated strategies? And which distinct groups can we identify based on these characteristics?

RQ2. Which topics interest the mentors?

RQ3. What is the relationship between mentor groups (*RQ1*) and the topics of interest?

4. Method

This section describes the case environment, the participants, the data collection and the data analysis.

4.1 Case environment: artificial intelligence family challenge

The organization is an engineering and technology education nonprofit organization, hosting a learning program that supports girls, children and their families in identifying problems in their communities, finding technology-based solutions and developing skills to become lifelong learners. The mission is to empower the world's underrepresented communities to become innovators and leaders through engineering and technology.

The setting of our study is an AI Family Challenge (a global competition). It targets students and their parents from around the world, whose goal is to learn about AI and then solve a problem in their community using AI technology. To that end, the program engages volunteer mentors to assist and support the families. Both the mentors and the mentees benefit: the mentees learn how to apply information management and problem-solving strategies and the mentors learn new technical content related to product development and launch, team management and connecting with diverse communities. Most importantly, they face new learning challenges personally and professionally.

4.2 Participants

The participants of our study are people who have volunteered to mentor families in the AI Family Challenge and have registered to participate in the preparatory online learning activities. They are professionals from industry and university partners with diverse backgrounds (engineering, education, business, professional services, etc.). The two main tasks of mentors were to participate in mentor training courses on an online platform (non-mandatory); helping families develop a prototype. The online mentor training consisted of 6 modules: families overview; technical communication; working with AI Tools; working with families (WF); helping families build prototypes; key AI and ideation concepts. We obtained data from 90 participants of which 82 completed a pre-survey and 8 took part in courses and responded to reflection questions (but not the pre-survey). Of 82 participants who completed the pre-survey, the majority had a professional degree: Bachelors (36), Masters or higher (39). Several participants (32) had a technical background, followed by education (27), business and professional services (12) and others.

4.3 Data collection and instruments

The data collection was accomplished through a self-assessment (pre-survey) regarding motivation, self-efficacy, ability to self-regulate and reflect and attitude toward lifelong learning and a reflection intervention concept (reflection questions) during mentor training to reflect about interests and to promote goal setting.

4.3.1 Pre-survey. A survey consisting of 42 questions was developed to assess the mentor's profiles at the beginning of the program. This survey was integrated into the online platform and placed before the online training modules. The responses were given as Very true for me (5) – True for me (4) – Quite true for me (3) – Sometimes true for me (2) to Not at all true for me (1). The survey included sections of demographic variables, attitude toward lifelong learning (7 items), motivation: intrinsic motivation, career motivation, self-efficacy (9 items) and self-regulated strategies: goal setting, strategic planning, critical thinking, help-seeking (HS), self-reflection (25 items).

The section on attitude toward lifelong learning followed the autonomous learning scale from Macaskill and Taylor (2010), a psychometrically valid instrument. From this lifelong learner autonomy perspective, the individuals take responsibility for their own learning, are motivated to learn, gain enjoyment from their learning, are open-minded, manage their time well, plan effectively, meet deadlines, are happy to work on their own, display perseverance when encountering difficulties and have low procrastination when it comes to their work (Macaskill and Taylor, 2010). This perspective is in line with our study, as this learning autonomy is reflected in the attitude toward lifelong learning, one of the positive mentor skills.

To assess the levels of motivation, we based our survey on the Science Motivation Questionnaire II from Glynn *et al.* (2011), as this questionnaire (based on the social cognitive theory), is a valid and efficient tool to assess the motivation components that are relevant for this study: intrinsic motivation, self-determination, self-efficacy and career motivation. The Science Motivation Questionnaire II was designed in the context of science students and we adapted the items to our context as one of the benefits of the mentoring program is to learn or expand the AI knowledge and skills.

Finally, to measure the level of self-regulated learning strategies, we based our survey on the questionnaire developed by Littlejohn *et al.* (2016) to obtain a self-regulated learning profile of the participants. The questionnaire is oriented toward professionals and includes relevant components for our study: goal setting, strategic planning, critical thinking, HS and self-reflection.

We took a complete construct for each aspect, adapting it to our context. The adaptations are necessary to make the questionnaire more understandable to our study participants. For example, for the construct motivation, an adapted item read as: "The mentoring makes my life more meaningful" rather than "Learning science makes my life more meaningful" as stated in the original questionnaire. For the construct self-regulated strategies, "I set personal standards for performance in my learning or job" replaced "I set personal standards for performance in my learning." For the construct of lifelong learning, "I take responsibility for my learning or training experiences" replaced "I take responsibility for my learning experiences."

We consider it relevant to assess – in a single instrument – motivation, attitude toward lifelong learning and self-regulated strategies to obtain more accurate results about these dimensions that we believe define the profile of a mentor.

Pre-survey consistency. A total of 82 volunteer participants completed the pre-survey. We validated the instrument through factor analysis. Factor correlations were strong between factors of the related scales, except for HS with weak to no correlations. Cronbach's alpha test for reliability confirmed the consistency of the constructs in the pre-survey: attitude toward life-long learning (LLL, alpha = 0.94), intrinsic motivation (IM, alpha = 0.91), career motivation (CM, alpha = 0.91), self-efficacy (SE, alpha = 0.84), goal-setting (GS, alpha = 0.81), strategic planning (SP, alpha = 0.78), critical thinking (CT, alpha = 0.76), help-seeking (HS, alpha = 0.46), self-reflection (SR, alpha = 0.79). A value of 0.7 or higher in Cronbach's alpha was considered indicative of good reliability. The results show that all constructs are consistent except HS. Therefore, answers to HS are not taken into account in the remainder of the analysis. Confirmatory factor analysis, after removing HS, revealed a good model fit ($\chi 2 = 175$, $p = 0.41$, RMSEA < 0.01, CFI = 0.97, TLI = 0.97) [1].

4.3.2 Reflection questions. There were six online training modules: families overview; technical communication; working with AI tools; WF; helping families build prototypes and key AI and ideation concepts. At the end of each module, the participants received two reflection questions:

Q1. What did you find interesting about the things that you did in this period (either in this training module or in volunteering with families)? Why?

Q2. Having identified interesting things in this period, can you set goals to apply a particular knowledge skill or attitude in your life, work or volunteering work with families?

For example:

- To practice brainstorming techniques with a problem in my area.
- To test two AI modules.

The above two reflection questions were inspired by Fleck and Fitzpatrick (2010), who proposed four qualities of reflection (description, reflective description, dialogic reflection and transformative reflection). The concept was extended in works such as Wolfbauer *et al.* (2020), applying a conversational agent to ask questions aiming to judge a past experience, raise awareness of the emotional positioning toward that experience, developing insights about it and planning for the future (Wolfbauer *et al.*, 2020).

In our study the goal and value of these questions to the study participants were to engage them in the reflection of learning content and interesting training elements and establish a link between the training and own private life or work to support learning (cp. Boud *et al.*, 1985, on reflection as supporting learning) and to increase their motivation by connecting the volunteer mentoring experience to other areas of life (cp. Littlejohn *et al.*, 2016 on the values of learning for professionals and Fessl *et al.*, 2018 on supporting the transfer of learning from an educational context to future work practice). These reflection questions also served as a research instrument, to elicit what was of particular interest to the participants.

Of a total of 90 participants doing the online modules, 51 answered some reflection questions.

4.3.3 Data analysis. Three types of analyzes were performed, in response to the research questions:

(1) Analysis of the pre-survey (bottom-up clustering) to build a mentor profile. With scores from the survey, a participant vector was created. By applying k-means to the participant's vector, we distinguished three groups with high, medium and low levels scores in the dimensions of the pre-survey. Clustering methods are used to assign sets of data into sub-groups (clusters), such that members of each cluster are more similar to members in the same cluster than to members of other clusters. As this is a bottom-up process (not guided by the experimenter), we have used the term "emerge" in this section to highlight that this structure was established via a standard data-driven procedure (machine learning methods).

(2) Content analysis of answers to the reflection questions. Content analysis is a systematic method to transform a large amount of text into a highly organized and concise summary of key results, to facilitate the discovery of significant themes (Erlingsson and Brysiewicz, 2017). We followed this methodology to extract topics of interest based on answers to the reflection questions.

(3) Analysis of topics of interest related to mentor's profile. A quantitative method was used to establish a relationship between mentions of the participant's topic of interest and their level of self-assessment (pre-survey). This was accomplished by comparing the number of mentions of each topic across the levels of self-assessment.

5. Results

This section describes the result of the analysis conducted to answer the three research questions.

5.1 Mentor's profile

To answer *RQ1* (What characterizes our study participants in terms of attitude toward lifelong learning, motivation and self-regulated strategies? And which distinct groups can we identify based on these characteristics?) we analyzed the answers to the pre-survey about the attitude toward lifelong learning (7 items), motivation (9 items) and self-regulated strategies (25 items) to build a mentor profile. To do so, a descriptor is created by averaging the scores within each construct. Finally, to establish the differences in terms of their levels, unsupervised clustering was applied.

5.1.1 Mentor's profile descriptor. After validating the consistency, a hybrid mentor profile was constructed as a vector describing a participant based on self-assessment in the pre-survey (Table 1).

The descriptor consists of a vector with a score for each dimension (lifelong learning, intrinsic motivation, career motivation, self-efficacy, goal setting, strategic planning, critical thinking and self-reflection) calculated as the mean of the responses to the survey questions. The analysis demonstrated high scores in all dimensions and high consistency across the participants, as illustrated in Figure 1. This makes it difficult to determine the profile groups by mere observation or by establishing simple thresholds. Therefore, we resorted to unsupervised methods for compiling groups of profiles.

5.1.2 Unsupervised clustering. Based on the participant vectors representing the mentor's profile, we intended to determine if they could be grouped and assigned to different levels. We applied several methods (elbow; silhouette and nbClust) to establish the optimal number of clusters. The results indicated that the optimal number of clusters was three. Preliminary analysis identified one outlier that was removed for further analysis (leaving 81 participants from 82 that answered the pre-survey).

Once the optimal number of clusters was obtained, we applied K-means to divide the participants into three groups according to their mentor's profile: G1 (low) with consistently lowest overall values; G2 (high) with extremely high values; G3 (medium) with slightly lower (medium) overall values. Note that despite our labeling the groups "high, medium and low," all groups had high average scores in all constructs of the pre-survey, as the participants were after all professionals who volunteered as mentors:

- Group 1 (G1, "low") had 19 participants. On a scale from 5 to 1, these participants scored between 3.5 and 4 in all of the pre-survey dimensions.
- Group 2 (G2, "high") had 46 participants. People in this group scored high on average in all dimensions. They were highly motivated, especially in terms of intrinsic and career motivation and highly capable of self-directed learning.
- Group 3 (G3, "medium") had 16 participants. People in this group scored high in all questions (between 4 and 5 in most dimensions) but consistently lower than the participants in G2. However, within the dimensions of the pre-survey, they scored especially high in IM (intrinsic motivation) (Figure 2).

Table 1.
Example of user vector

Uid	LLL	IM	CM	SE	GS	SP	CT	SR
2	4.85	5.0	4.6	5.0	4.0	4.50	4.66	5.0

Notes: User number (Uid), lifelong learning (LLL), intrinsic motivation (IM), career motivation (CM), self-efficacy (SE), goal setting (GS), strategic planning (SP), critical thinking (CT) and self-reflection (SR)

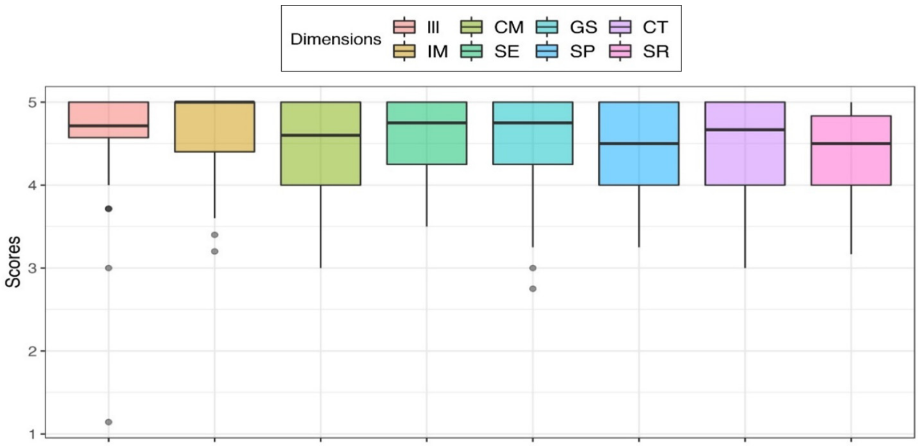

Figure 1.
Scores of participants in all of the pre-survey dimensions: lifelong learning (LLL), intrinsic motivation (IM), career motivation (CM), self-efficacy (SE), goal setting (GS), strategic planning (SP), critical thinking (CT), self-reflection SR)

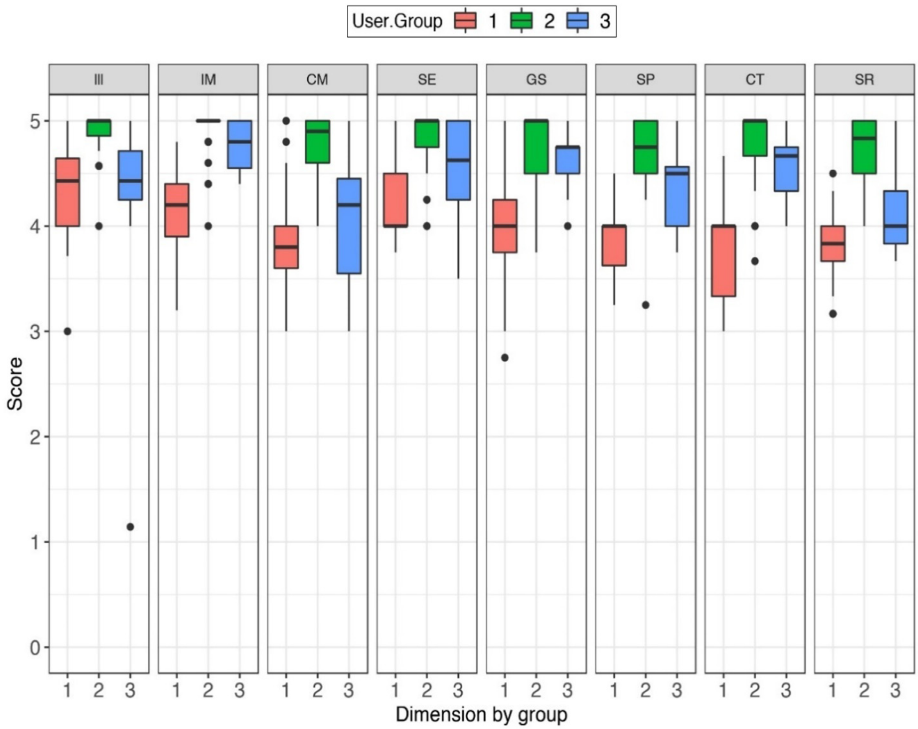

Figure 2. Groups of participants (user groups = mentor groups) and scores in all of the pre-survey dimensions: lifelong learning (LLL), intrinsic motivation (IM), career motivation (CM), self-efficacy (SE), goal setting (GS), strategic planning (SP), critical thinking (CT), self-reflection (SR)

5.2 Topics of interest

To answer *RQ2* (What topics interest mentors?), we applied a content analysis methodology to analyze answers to the reflection questions and to extract topics of interest.

5.2.1 Content analysis. Content analysis consisted of breaking down the data to transform a large amount of text into meaning units, codes and themes, to ultimately determine the topics of interest. The data consisted of answers to two reflection questions that the participants provided at the end of specific courses on the platform. The data were obtained from a spreadsheet stating the course name, the question and the response. To extract the topics of interest from this qualitative data, we followed the steps presented in Erlingsson and Brysiewicz (2017):

(1) Meaning units: each answer is condensed to capture its core meaning. The condensation should be a shortened version of the same text that still conveys the essential message of the meaning unit. Examples of two answers and their condensation in meaning units.

- The possibility of establishing family communication around AI learning and why an activity like this allows parents and children to learn from each other (Interacting with families and learning from others).
- I'm really excited to become part of this community, I really love the idea of helping families deal with this kind of challenge [. . .] (Helping families deal with challenges).

(2) Codes: distinctive phrases are assigned as codes to assign descriptive labels for the condensed meaning units. These phrases are used as a means to identify connections between the meaning units. The following code illustrates the process of grouping the meaning units using codes (Tables 2 and 3).

(3) Category: categories are a covert organization of the content that is developed by analyzing which codes seem to belong together. Category names are most often short and factual-sounding. Categorization scheme. Example of first category working with families

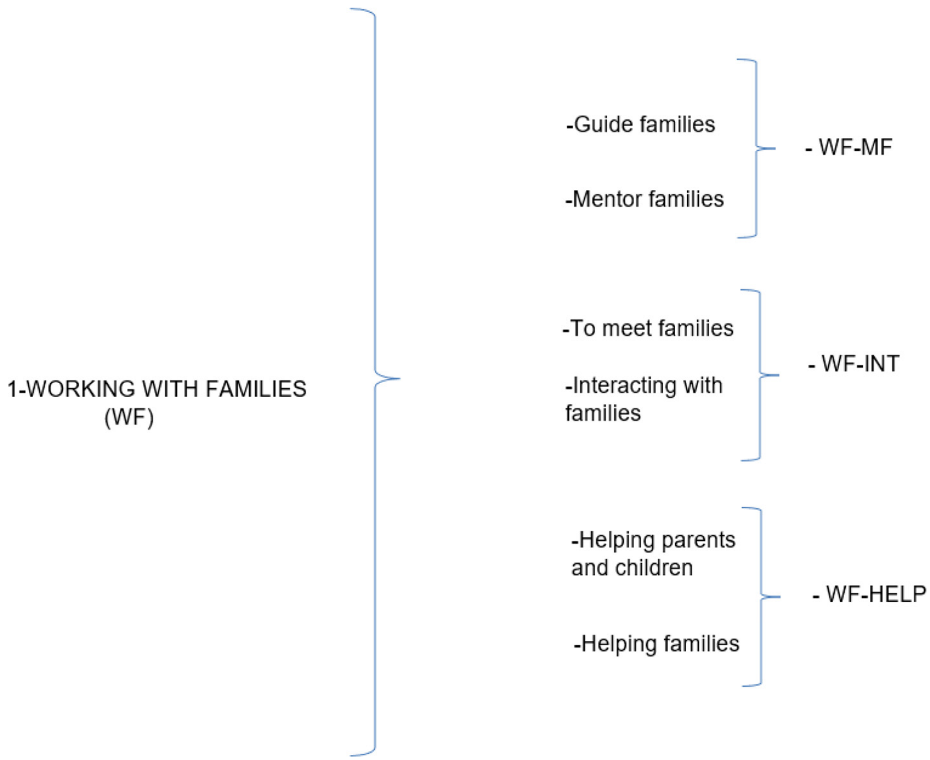

Table 2. Example of codes developed from reflection question 1 about finding interesting things

Codes/themes	Examples
- Interacting with families	- *Interacting with the children and their parents…* - *The most interesting thing for me was working with families…*

The process described above was performed to identify the meaning units, codes and categories. The categorization scheme was applied to determine topics of interest. This analysis revealed the following emerging interesting topics or goals for the future:

Communication skills (CM): refers to the interest in practicing or improving communication skills:

> "It helped me develop my communication and mentoring skills." "To build, practice and improve communications skills."

Learning AI (LAI): refers to the interest to learn about AI concepts for personal or professional development and to teach others:

> "It is a learning experience for all of us, mentors and participants. I am interested to learn about AI and excited to learn with more curious people like me."

Mentoring (MENT): refers to the interest in helping others with and mentoring others on AI technology:

> "How to effectively mentor another person on the AI technology and skills."

Prototype development (PROT): refers to the interest in developing prototypes to solve technological solutions and helping the families with this task:

> "I'm excited about starting the program and trying to build prototypes by myself so that I will be confident about mentoring families."

Problem-solving skills (PSS): refers to the interest in developing PSS, identifying problems to solve using technology, using AI concepts to solve problems:

> "To develop problems solving skills."

Working with families (WF): refers to the interest in helping and WF on the challenges:

> "I really love the idea of helping families deal with this kind of challenge, help them to feel confident to solve problems they face by using technology."

5.2.2 Topics mentioned in reflection questions. To determine the topics most mentioned in the answers during the reflection, frequency analysis on the answers was carried out using the topic categories as a proxy. Table 4 shows the results of frequency analysis, with the total number of times a topic was mentioned, the average (mean) number of times a topic was mentioned per participant and the standard deviation. Subsequently, an analysis of variance (ANOVA) test was conducted to find out what topic was mentioned most in the answers to the reflection questions.

An Analysis of variance test between topics revealed significant differences in the number of mentions of a specific topic [$F(6,350) = 4.342$, $p < 0.0001$]. Tukey HSD posthoc comparisons revealed significant differences: WF was mentioned by more participants ($p < 0.0001$) (M = 1.41) than prototyping (M = 0.57), mentoring (M = 0.55) and communication

Table 3. Example of codes developed based on reflection question 2 about setting goals

Codes/themes	Examples
– To test out AI	– *To test out specific AI modules* – *Work on practicing the various AI models*

(M = 0.43). LAI was mentioned in more answers ($p < 0.0001$) (M =1.27) than communication (M = 043). Summing up, the topics WF and learning AI were the most mentioned topics in the answers to the reflection questions (see confidence intervals in Figure 3).

5.3 Relating topic of interest and groups

To answer *RQ3* (What is the relationship between mentor groups and topics of interests?), in Section 5.3.1 we first estimated a measure of engagement by counting the answers to the reflection questions accumulated by each group. Section 5.3.2 describes how we related the groups and the topics of interest (identified through content analysis) to determine the most prominent topic of interest for each group.

5.3.1 Descriptive statistics. This analysis aimed to establish how much each group was engaged in answering the reflection questions. To that end, we calculated the average number of answers per participant in each group. Our data included a total of 182 answers. Of 81 participants who answered the pre-survey and had a participant vector, 43 answered some reflection questions. In addition, 8 participants – who did not answer the pre-survey – also

Table 4.
Topics mentioned in reflection questions

Topic	Freq.	Mean (n = 51)	SD
WF	72	1.41	1.55
LAI	65	1.27	2.1
PROT	29	0.57	1.08
PSS	41	0.8	1.11
MENT	28	0.55	0.88
COM	22	0.43	0.88

Notes: Freq. = The total number of times a topic was mentioned in answers to reflection questions. Mean refers to the average mentions per participant that answered at least one question. SD: standard deviation

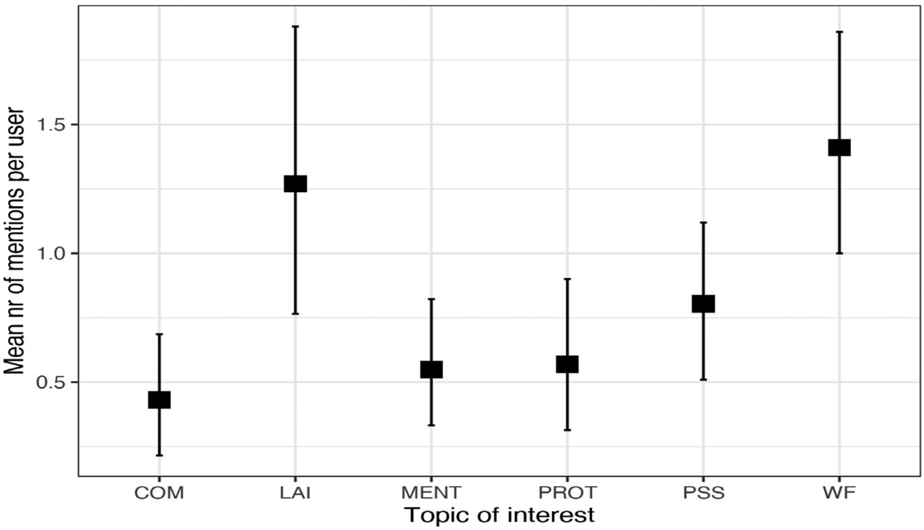

Figure 3.
Topics of interest and the mean nr. of mentions per user. WF: working with families; LAI: learning AI; PROT: prototype develop; PSS: problem-solving skills; MENT: mentoring; COM: communication skills

answered reflection questions. Therefore, a total of 51 participants answered the reflection questions. The 8 new participants were assigned to Group 4, G4 "new" (Table 5).

Table 5 summarizes information about answers to the reflection questions per group. The table shows answers to the pre-survey by group and the total number of participants in each group. It also indicates the number of participants that actually answered the reflection questions. The average number of answers per participant was calculated taking into account the participants that actually answered some questions. While G3 "medium" tended to have more questions per participant, a Kruskall–Wallis test revealed no statistically significant difference. Therefore, it was assumed that all groups answered an equal number of reflection questions on average.

5.3.2 Relating groups and topic of interest. To investigate the relationships between the groups and the topics of interest, we posed two questions:

Q1. Do the groups differ in terms of the number of mentions per topic?

Q2. In every group, how often was each topic mentioned and what were the most mentioned interests in a group?

The answers of each participant were coded based on the topics extracted. Hereby, it was possible to count the number of mentions of each topic per participant and group. Figure 4 shows the distribution of the topic mentions for each group.

As the groups had a different number of participants and gave a different number of responses, Kruskall–Wallis followed by Dunn's pairwise comparison tests were used. The number of mentions each participant gave for each topic was normalized to compare the proportion of the topic between groups. Comparing the number of mentions across groups, statistical differences were found between the groups only for the mentions of the topic WF. The Kruskall–Wallis test revealed significant differences [$X2(3) = 13.061$, $p < 0.005$]. Dunn's pairwise comparison showed that G3 had significantly more mentions of the topic "Working with families" than G1 ($p < 0.05$) and G2 $p < 0.001$ (Figure 5).

The most prominent topics of interest for each group were determined by comparing the number of mentions between the topics within a group. From Figure 4 it is possible to make the following observations:

G1 (low): The topics of interest are more distributed. The Kruskall–Wallis test showed no significant difference in the number of mentions per topic of interest.

G2 (high): The Kruskall–Wallis test revealed significant differences in the number of mentions per topic of interest [$X2(5) = 22.872$ $p < 0.001$]. Dunn's pairwise comparison showed that WF

Table 5. Groups of participants (who answered the pre-survey), total participants, participants who answered the reflection questions and number of answers per group

Group	Pre-survey	No. of answers per group	Total participants	Participants answering reflection questions	Average of answers per participant
1 "low"	Yes	33	19	10	3.3
2 "high"	Yes	102	46	27	3.78
3 "medium"	Yes	29	16	6	4.83
4 "new"	No	18	8	8	2.25

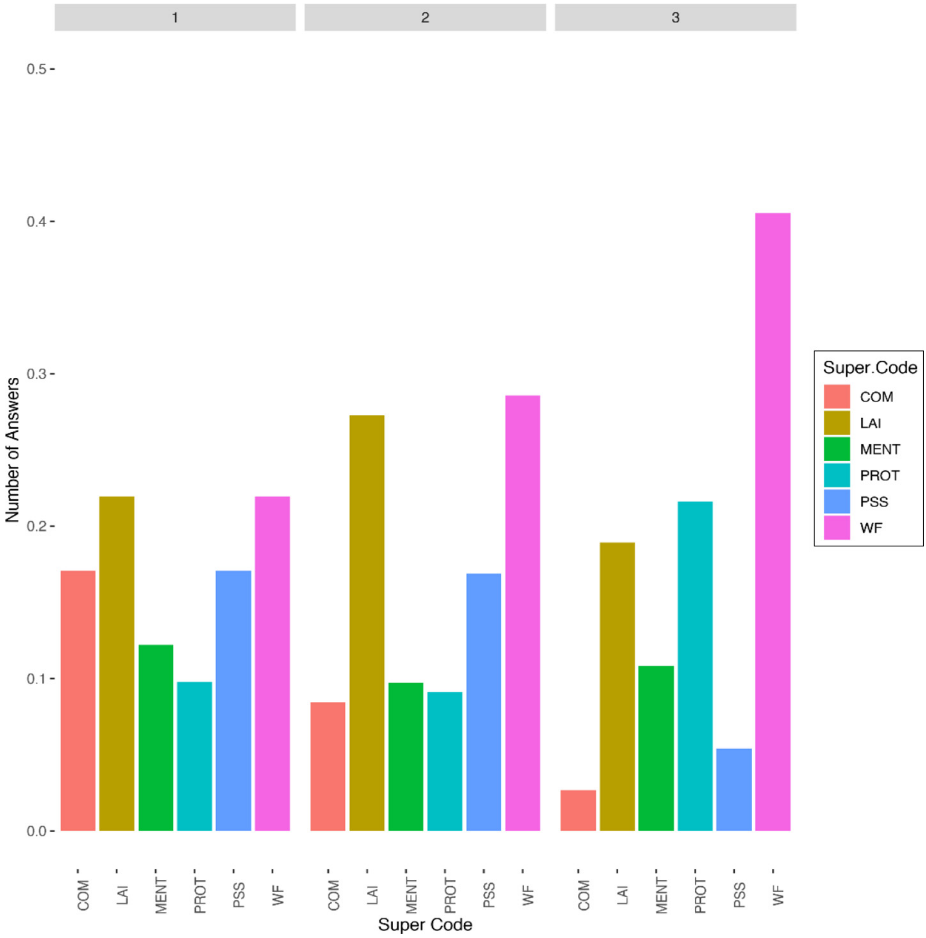

Figure 4.
Topics of interests and number of answers per group (1, 2, 3). COM: communication skills; LAI: learning AI; MENT: mentoring; PROT: prototype develop; PSS: problem-solving skills; WF: working with families

appeared in responses of this group more than mentoring (MENT, $p < 0.01$), communication (COM, $p < 0.01$) and prototyping (PROT, $p < 0.01$). While the total number of mentions was high for the topic of learning AI, these were made by a small number of participants in the group, indicating high variability and failing to reach significance. Conversely, WF was consistently mentioned in the answers of the group members.

G3 (medium): The interest focuses on WF and develops a prototype (PROT). The Kruskal–Wallis test revealed significant differences in the number of mentions per topic of interest [X2(5) = 22.872 $p < 0.05$]. Dunn's pairwise comparison showed that WF appeared in the responses of this group more than communication (COM, $p < 0.01$).

It must be noted that these analyzes are constrained by the number of responses. The data preparation and selection of tests were applied to ensure appropriate application thereof.

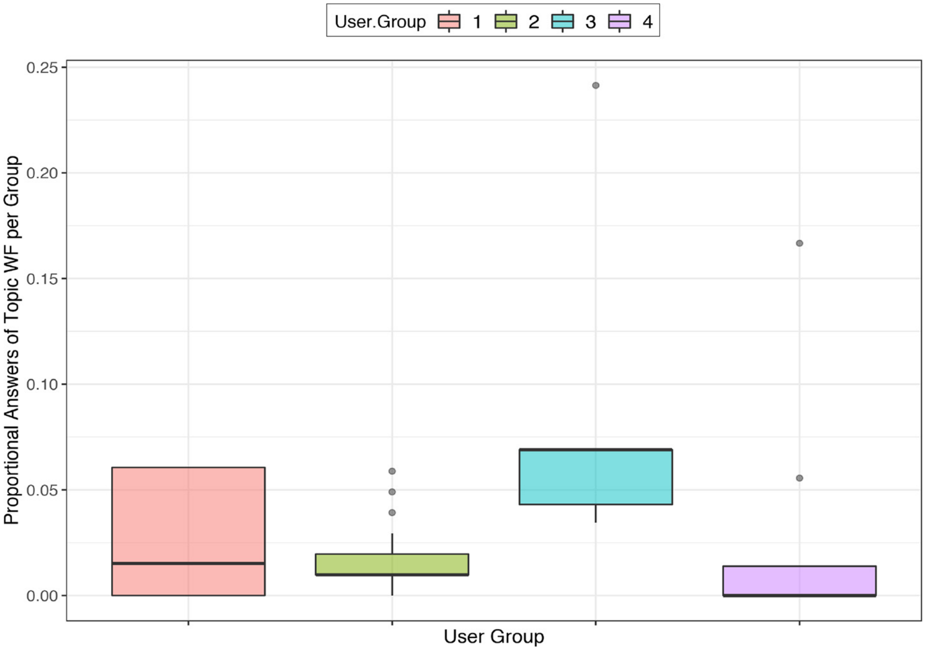

Figure 5.
Proportional mentions of topic WF (working with families) per group

6. Discussion and conclusions

This study provides an analysis of volunteer mentors based on self-assessments of motivation, attitude toward lifelong learning and self-regulated learning strategies that were used to create a mentor's profile; learning interests in the sense of volunteer mentors' topic-specific interests and goals for own learning and development through the participation in the mentoring program and the relationship between mentor's profile and interests.

The first analysis aimed to answer *RQ1*: What characterizes our study's participants in terms of attitude toward lifelong learning, motivation and self-regulated strategies? And which distinct groups can we identify based on these characteristics? We calculated scores for each participant in each dimension of the pre-survey. The scores evidenced quite homogeneous distribution, which makes it difficult to discriminate patterns visually or set a threshold. Therefore, a participant's vector was built using the dimensions describing a hybrid user profile. Applying K-means made it possible to identify three groups of participants. One outcome of this report is the methodology used to elicit the levels of these dimensions and aggregate them in a descriptor that can be used to differentiate groups of participants (low, medium and high) that are otherwise not visible.

The second analysis aimed to answer *RQ2*: What topics interest the mentors? We analyzed the answers to two reflection questions, whose goal was to identify the elements of mentoring that are interesting and useful in private and professional lives. Applying content analysis, the topics of interest were extracted. The results showed that the topics WF and learning AI were the most mentioned ones.

The third analysis aimed to answer *RQ3*: What are the relationship between the mentor groups (see *RQ1*) and the topics of interest? By comparing the number of mentions of topics across the groups, it was established that one group (G3, medium) focused significantly more on the topic WF than the other two groups (Figure 5). G3 (medium) revealed a high intrinsic motivation, which drives activities that are undertaken for the enjoyment and inherent satisfaction of performing a specific task. They prioritize intrinsic motivational aspects over career motivation. In turn, G2 (high) was more interested in learning AI, WF and developing PSS, which correspond to particularly high scores in intrinsic motivation and also in career motivation. In this sense, it can be interpreted that they are not only interested in the experience of WF but also in learning and developing skills that will benefit their careers.

These analyzes and results are aligned with the work of Kizilcec *et al.* (2013), Kizilcec and Schneider (2015); Kizilcec *et al.* (2017), Littlejohn *et al.* (2016) and Cicchinelli *et al.* (2018). These studies assessed the level of self-regulated learning (SRL) strategies and motivation and established discernible differences between the participants with higher and lower SRL scores. They relate the scores to the engagement or performance, the level of SRL strategies and the type of motivation for enrolling into a MOOC or specifically assessed motivation as a lens for understanding learners to better support their needs (Kizilcec and Schneider, 2015).

Our work also aligns with the work of Margaryan *et al.* (2013), who used interview questions to understand the ways in which professionals set and attain their learning and development goals associated with the completion of a project/task. To extend this work on understanding SRL strategies, motivation and attitude toward lifelong learning in MOOC settings, our study adds the relationship between the participant's profile in terms of SRL strategies, motivation and attitude toward lifelong learning and topics of interests extracted from his/her reflection during learning in the context of volunteer work. Our method serves as a basic building block for the organization to better adapt the offer to the needs of the participants, e.g. via study materials on reflection strategies or self-regulated learning besides the content targeting the interests of mentors.

Furthermore, with regard to the mentoring literature, according to Bortnowska and Seiler (2019), there are few studies on mentoring in non-profit organizations and the focus is on the effects of mentorship on career progression and the benefit to the organization. Our work adds a detailed analysis of the diverse types of interests leading a participant to engage in mentoring. We also make a methodological contribution; mentoring literature tends to be based on surveys or interviews to understand mentors' motives (Allen *et al.*, 1997; Allen, 2003; Allen and Eby, 2003; Day and Allen, 2004; Janssen *et al.*, 2014). The reflection questions used in this work to elicit the mentor's interests could be valuable directly to volunteers and mentors by supporting reflection and transfer of learning between contexts and to organizations that facilitate volunteering and mentoring as a measurement instrument to elicit interests and content-wise motivation.

The limitations of our work arise from its context and types of participants. First of all, the training program was not mandatory. This means that our sample of study participants could have been biased toward highly motivated ones and those open to using the mentoring experience as a learning experience. Second, this study does not systematically follow up on how the interests of mentors found during the preparatory training changed or developed throughout the mentoring experience.

This is one avenue of future research that we consider highly interesting, namely, to study the developing interests of volunteer mentors before and during mentoring, as well as their changing perception, attitude and capability to use mentoring as a learning experience and its value to other areas of life. Additionally, this work addresses one design rationale for a reflection intervention with questions that prompt reflection by engaging the mentors in the reflection. A reflection intervention could support the mentors' motivation by making them aware of the insights that could be transferred to their professional or private life. In future research, we would like to investigate different formulations of reflection prompts and their effects on motivation, as other researchers have shown that details of phrasing can have significant effects (Renner *et al.*, 2016).

With respect to using the reflection questions as a knowledge-gathering instrument (which would be valuable to organizations aiming to understand and enhance volunteers' benefits from volunteering), one limitation is that content analysis is time-consuming and requires the engagement of experts. For a continuous application of this method, (semi-) automated methods of topic extraction or topic modeling should be investigated.

Note

1. χ^2 test should be non-significant. Acceptable cut-off values: CFI > 0.96, TLI > 0.95, RMSEA < 0.05.

References

Alario-Hoyos, C., Estévez-Ayres, I., Pérez-Sanagustín, M., Dlegado Kloos, C. and Fernández-Panadero, C. (2017), "Understanding learners' motivation and learning strategies in MOOCs", *International Review of Research in Open and Distributed Learning*, Vol. 18 No. 3, pp. 119-137.

Allen, T.D. (2003), "Mentoring others: a dispositional and motivational approach", *Journal of Vocational Behavior*, Vol. 62 No. 1, pp. 134-154.

Allen, T.D., Eby, L.T. (2003), "Relationship effectiveness for mentors: factors associated with learning and quality", *Journal of Management*, Vol. 29 No. 4, pp. 469-486.

Allen, T.D., Poteet, M.L., Russell, J.E.A. and Dobbins, G.H. (1997), "A field study of factors related to supervisors' willingness to mentor others", *Journal of Vocational Behavior*, Vol. 50 No. 1, pp. 1-22.

Allison, L.D., Okun, M.A. and Dutridge, K.S. (2002), "Assessing volunteer motives: a comparison of an open-ended probe and Likert rating scales", *Journal of Community and Applied Social Psychology*, Vol. 12 No. 4, pp. 243-255.

Bandura, A. (1994), "Self-efficacy", in Ramachaudran, V.S. (Ed.), *Encyclopedia of Human Behavior*, Vol. 4, Academic Press, New York, NY, pp. 71-81. (Reprinted in H. Friedman [Ed.], Encyclopedia of mental health. San Diego: Academic Press (1998).

Bogdanova, M. (2008), "Cross-national mentoring NGOs in transition societies: field research and developments in Bulgaria", *Journal of Business Economics and Management*, Vol. 9, pp. 145-154.

Bortnowska, H. and Seiler, B. (2019), "Formal mentoring in nonprofit organizations. Model proposition", *Management*, Vol. 23 No. 1, pp. 188-208.

Boud, D., Keogh, R. and Walker, D. (1985), *Promoting Reflection in Learning: A Model. Reflection: Turning Experience into Learning*, Routledge Falmer, New York, NY, pp. 18-40.

Cicchinelli, A., Veas, E., Pardo, A., Pammer-Schindler, V., Fessl, A., Barreiros, C. and Lindstaedt, S. (2018), "Finding traces of self-regulated learning in activity streams", *Proceedings of the 8th Int. Conf. on Learning Analytics and Knowledge (LAK '18)*, ACM, *New York, NY*, pp. 191-200.

Clary, E.G. and Snyder, M. (1999), "The motivations to volunteer: theoretical and practical considerations", *Current Directions in Psychological Science*, Vol. 8 No. 5, pp. 156-159.

Clary, E.G., Snyder, M., Ridge, R.D., Copeland, J., Stukas, A.A., Haugen, J. and Miene, P. (1998), "Understanding and assessing the motivations of volunteers: a functional approach", *Journal of Personality and Social Psychology*, Vol. 74 No. 6, pp. 1516-1530.

Collins, J. (2004), "Education techniques for lifelong learning", *RadioGraphics*, Vol. 24 No. 5, pp. 1483-1489.

Day, R. and Allen, T.D. (2004), "The relationship between career motivation and self-efficacy with protégé career success", *Journal of Vocational Behavior*, Vol. 64 No. 1, pp. 72-91.

Erlingsson, C. and Brysiewicz, P. (2017), "A hands-on guide to doing content analysis", *African Journal of Emergency Medicine*, Vol. 7 No. 3, pp. 93-99.

Fessl, A., Wesiak, G. and Pammer-Schindler, V. (2018), "Transfer of theoretical knowledge into work practice: a reflective quiz for stroke nurses", *Knowledge Management in Digital Change*, Springer, Cham, pp. 291-308.

Finkelstien, M.A. (2009), "Intrinsic vs extrinsic motivational orientations and the volunteer process", *Personality and Individual Differences*, Vol. 46 Nos 5/6, pp. 653-658, ISSN 0191-8869.

Fleck, R. and Fitzpatrick, G. (2010), "Reflecting on reflection: framing a design landscape", *Proceeding of. Australian Conference. on HCI OZCHI 2010*, ACM, *New York, NY*, pp. 216-223.

Glynn, S., Brickman, P., Armstrong, N. and Taasoobshirazi, G. (2011), "Science motivation questionnaire II: validation with science majors and nonscience majors", *Journal of Research in Science Teaching*, Vol. 4 No. 10, pp. 1159-1176.

Janssen, S., van Vuuren, H.A. and de Jong, M.D.T. (2014), "Motives to mentor: self-focused, protégé-focused, relationship-focused, organization-focused, and unfocused motives", *Journal of Vocational Behavior*, Vol. 85 No. 3, pp. 266-275.

Jovanović, J., Gašević, D., Dawson, S., Pardo, A. and Mirriahi, N. (2017), "Learning analytics to unveil learning strategies in a flipped classroom", *The Internet and Higher Education*, Vol. 33, pp. 74-85.

Kirby, J.R., Knapper, C., Lamon, P. and Egnatoff, W.J. (2010), "Development of a scale to measure lifelong learning", *International Journal of Lifelong Education*, Vol. 29 No. 3, pp. 291-302.

Kizilcec, R.F. and Schneider, E. (2015), "Motivation as a lens to understand online learners: toward data-driven design with the OLEI scale", *ACM Transactions on Computer-Human Interaction*, Vol. 22 No. 2, p. 6.

Kizilcec, R.F., Piech, C. and Schneider, E. (2013), "Deconstructing disengagement: analyzing learner subpopulations in massive open online courses", *Proceedings of the Third International Conference on Learning Analytics and Knowledge (LAK '13)*, Association for Computing Machinery, *New York, NY*, 170-179.

Kizilcec, R.F., Pérez-Sanagustín, M. and Maldonado, J.J. (2017), "Self-regulated learning strategies predict learner behavior and goal attainment in massive open online courses", *Computers and Education*, Vol. 104, pp. 18-33.

Littlejohn, A., Milligan, C. and Margaryan, A. (2012), "Charting collective knowledge: supporting self-regulated learning in the workplace", *Journal of Workplace Learning*, Vol. 24 No. 3, pp. 226-238.

Littlejohn, A., Hood, N., Milligan, C. and Mustain, P. (2016), "Learning in MOOCs: motivations and self-regulated learning in MOOCs", *The Internet and Higher Education*, Vol. 29, pp. 40-48.

Macaskill, A. and Taylor, E. (2010), "The development of a brief measure of learner autonomy in university students", *Studies in Higher Education*, Vol. 35 No. 3, pp. 351-359.

Margaryan, A., Milligan, C. and Littlejohn, A. (2013), "Self-regulated learning in the workplace: strategies and factors in the attainment of learning goals", *International Journal of Training and Development*, Vol. 17 No. 4, pp. 245-259.

Margaryan, A., Milligan, C., Littlejohn, A., Hendrix, D. and Graeb-Koenneker, S. (2009), "Self-regulated learning and knowledge sharing in the workplace", *Organizational Learning, Knowledge and Capabilities Conference*, *Amsterdam*.

Momoh, G.T., Oluwasanu, M.M., Oduola, O.L., Delano, G.E. and Ladipo, O.A. (2015), "Outcome of a reproductive health advocacy mentoring intervention for staff of selected, non-governmental organisations in Nigeria.", *Health Services Research*, Vol. 15 No. 1, pp. 1-9.

Nyamori, S. (2015), "The effect of workplace mentoring on employee performance: a case study of SOS Children's Villages", *United States International University Africa.*.

Pardo, A., Han, F. and Ellis, R.A. (2016), Exploring the relation between self-regulation, online activities, and academic performance: a case study, *Proceedings of the Sixth International Conference on Learning Analytics and Knowledge (LAK '16).* ACM, *New York, NY*, pp. 422-429.

Renner, B., Prilla, M., Cress, U. and Kimmerle, J. (2016), "Effects of prompting in reflective learning tools: findings from experimental field, lab, and online studies", *Frontiers of Psychology*, Vol. 7, p. 820.

Ryan, R.M., Deci, E.L. (2000), "Intrinsic and extrinsic motivations: classic definitions and new directions", *Contemporary Educational Psychology*, Vol. 25 No. 1, pp. 54-67, ISSN 0361-476X.

Smith, W.J., Howard, J.T. and Harrington, K.V. (2005), "Essential formal mentor characteristics and functions in governmental and non-governmental organizations from the program administrator's and the mentor's perspective", *Public Personnel Management*, Vol. 34 No. 1, pp. 31-58.

Snyder, M., Clary, E.G. and Stukas, A.A. (2000), "The functional approach to volunteerism", in Maio, G.R. and Olson, J.M. (Eds), *Why we Evaluate: Functions of Attitudes*, Lawrence Erlbaum Associates, Hillsdale, NJ, pp. 365-393.

Thoits, P. and Hewitt, L. (2001), "Volunteer work and well-being", *Journal of Health and Social Behavior*, Vol. 42 No. 2, pp. 115-131.

Voyles, E., Kowalchuk, R., Nicklow, J. and Ricks, R. (2011), Residential peer mentoring benefits mentees: what about mentors?, *ASEE Annual Conference*, *Vancouver, BC.*

Washington, D. (2011), "Mentoring and career progression in the nonprofit sector", *Leadership & Organizational Management Journal*, No. 1, pp. 50-62.

Wilson, J. (2000), "Volunteering", *Annual Review Sociology*, Vol. 26 No. 2, pp. 15-40.

Wolfbauer, I., Pammer-Schindler, V. and Rosé, C. (2020), "Rebo junior: analysis of dialogue structure quality for a reflection guidance chatbot", *EC-TEL Impact Paper Proceedings 2020, CEUR Workshop Proceedings*.

Zimmerman, B.J. (2000), "Attaining self-regulation: a social cognitive perspective", in Boekaerts, Monique, Pintrich, Paul R. and Zeidner, Moshe (Eds), *Handbook of Self-Regulation*, pp. 13-39, ISBN 9780121098902.

Further reading

Allen, T.D., Lentz, E. and Day, R. (2006), "Career success outcomes associated with mentoring others: a comparison of mentors and non mentors", *Journal of Career Development*, Vol. 32 No. 3, pp. 272-285.

Boekaerts, M., Zeidner, M. and Pintrich, P.R. (Eds) (2000), *Handbook of Self-Regulation*, Academic Press, San Diego, CA, pp. 13-39.

Fessl, A., Blunk, O., Prilla, M. and Pammer, V. (2017b), "The known universe of reflection guidance: a literature review", *International Journal of Technology Enhanced Learning*, Vol. 9 Nos 2/3, pp. 103-125.

Fessl, A., Wesiak, G., Rivera-Pelayo, V., Feyertag, S. and Pammer-Schindler, V. (2017a), "In-App reflection guidance: lessons learned across four field trials at the workplace", *IEEE Transactions on Learning Technologies*, Vol. 10 No. 4, pp. 488-501.

Fontana, R., Milligan, C., Littlejohn, A. and Margaryan, A. (2015), "Measuring self-regulated learning in the workplace", *International Journal of Training and Development*, Vol. 19 No. 1, pp. 32-52.

Kirkpatrick, D. (1994), *Evaluating Training Programs*, Berrett-Koehler Publishers, San Francisco, CA.

Moreno-Marco, P., Munioz Merino, P., Maldonado-Mahauad, J., Pérez Sanagustín, M., Alario-Hoyos, C. and Delgado Kloos, C. (2020), "Temporal analysis for dropout prediction using self-regulated learning strategies in self-paced MOOCs", *Computers and Education*, Vol. 145, p. 103728.

Pintrich, P. and De Groot, E. (1990), "Motivational and self-regulated learning components of classroom academic performance", *Journal of Educational Psychology*, Vol. 82 No. 1, p. 33.

Corresponding author
Analia Cicchinelli can be contacted at: cicchinelli@tugraz.at