IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 7 November 2023, accepted 26 December 2023, date of publication 8 January 2024, date of current version 16 January 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3351098

RESEARCH ARTICLE

Emergency Remote Teaching in Higher Education Institutes: A Taxonomy of Challenges Faced by First-Year Mathematics Students in the Pacific Region

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ABSTRACT Emergency Remote Teaching (ERT) can be defined as a shift of instructional delivery to a substitute delivery approach during a crisis. Such a shift poses several challenges for students at Higher Education Institutes. This paper presents a taxonomy of such challenges faced by first-year mathematics students in the Pacific region during the ERT dictated by the COVID-19 pandemic. First, a list of 44 challenges was assembled based on a university's in-house monitoring report, literature review and the authors' experiences of challenges faced by students. Next, the open card sorting technique involving 32 participants was used to classify these challenges. Open card sorting is a well-established method for discovering how people understand and categorize information. This paper employed a recently proposed algorithm to quantitatively analyze open card sorting data using the Best Merge Method, Category Validity Technique and Multidimensional Scaling. Analysis of the collected card sort data produced the initial taxonomy of challenges. Finally, the participants were asked to answer a questionnaire so that we could validate and further refine the taxonomy. The proposed taxonomy includes seven challenges: i) lack of online learning support; ii) problem with online course delivery; iii) time and workload management; iv) learning management system issues; v) lack of face-to-face interaction; vi) financial hardship; vii) internet challenge. Such a taxonomy might be particularly useful in designing and evaluating an ERT approach.

INDEX TERMS Best merge method (BMM), card sorting, category validity technique (CVT), COVID-19 pandemic, emergency remote teaching (ERT), mathematics.

I. INTRODUCTION

The education institutes worldwide went from face-to-face and hybrid learning to complete online learning [1] during the COVID-19 pandemic. Many Higher Education Institutes (HEIs) worldwide had to make a sudden shift to online instruction and delivery. The abrupt transition to online instruction was widely termed as Emergency Remote Teaching (ERT) due to the challenges caused by the outbreak [1]. The global shift to ERT and its actual application using online platforms and systems delivering various services garnered many unexpected challenges that students, teachers, parents and institutions were not adequately prepared for [1], [2], [3], [4], and [5]. This included issues regarding technology (infrastructure, competencies etc), home learning environment, Internet network capacity, and time conflicts between work and online learning sessions [6]. Students complained about difficulties in gaining access to educational resources and completing online activities and assessments, whilst facilitators and universities were concerned with the lack of student engagement in an ERT learning environment [7].

Many challenges were invariably faced, highlighted and recorded during the COVID-19 lock-down regarding the unpreparedness of universities, ICT competencies across a

The associate editor coordinating the review of this manuscript and approving it for publication was S. Chandrasekaran.

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university, availability of relevant technologies, staff and students' ability to cope with the stress and build resilience while following precautions for preventive purposes. The term challenge is stipulated in this paper as the difficulties, problems or issues that affect students' learning ability during ERT. There were no learning systems nor teaching plans in place to cater for emergency needs in a pandemic, prompting widespread confusion and adhoc actions and reactions. Every action was rushed, and people got confused while attempting to keep ERT going while adapting to these challenges.

The challenges of supporting learner interests and understanding through online education are well-documented. They include the feeling of disconnection [8], the difficulty in meeting individual learning needs [9] and the lack of self-direction [10]. These challenges were exacerbated during the pandemic when many educators and learners were suddenly immersed in unfamiliar and unaffordable situations [11] and new technologies. While various such challenges have been identified by several studies, the existing literature hasn't categorized (taxonomized) them into more general categories (taxonomy), which represent groups of similar challenges. For example, "financial hardship" is a high-level challenge category to represent "Internet price is expensive", "no /limited money to purchase Internet data", "cannot afford to buy the textbook", "expensive to buy relevant software" etc.

Motivated by this gap in the literature, this paper presents a unique taxonomy of challenges that first-year mathematics students faced during the unexpected shift to ERT due to COVID-19 lockdown restrictions in a regional university. The initial set of challenges was collected from a university's in-house monitoring report, literature review [1], [2], [12], [13], [14], [15] and the authors' experiences. These challenges were organized into a taxonomy by employing Open Card Sorting (OCS) [16], a method of eliciting mental models from participants, and analyzing the collected data using innovative algorithms that have been recently proposed in the literature [17] and [18]. The proposed taxonomy can be used to improve ERT in HEIs, especially in the field of mathematics education during a pandemic.

The main contributions of this paper are as follows:

1) Successful introduction of the card sorting method in the field of educational research. This method can provide valuable insights into students' mental models on various topics. In our case, it enabled a deeper understanding of the learning challenges faced by first-year mathematics students during emergencies and crises, for Pacific and beyond. The implication is that such a deeper understanding of these challenges can help education stakeholders design better student-oriented learning support models for specific situations and targeted needs, and facilitate the design of tailored online courses and other contextualized learning resources.
2) Design of a unique seven-category taxonomy model to better comprehend and explain the complex nature of mathematics students' learning experiences in a Pacific regional university, calling for a more inclusive, affordable, and sustainable ERT. The model can be applied in any learning environment, especially in ERT situations, with special attention given to learners' dynamic, socio-cultural backgrounds that should include contextualization.

The paper consists of seven sections, including this introductory section. The next two sections provide a brief description of the literature review and the data collection methods. This is followed by data analysis in section four. Section five presents and discusses the findings, followed by the final category taxonomy for participants' challenges in section six. The final section concludes the paper.

II. LITERATURE REVIEW

Recent studies on ERT highlight different types of challenges experienced by students during the unexpected educational shift (e.g., [1], [2], [12]). A study that explored students' lived experiences as impacted by the emergency shift to remote teaching in the USA confirmed that students with existing educational inequality had been exposed to more learning inequalities during the abrupt shift to ERT [5], [12]. Students had to provide their own learning resources, which put them at a great disadvantage in relation to the unsafe learning environment, poor access to the Internet and inability to possess electronic devices. Students who do not have access to laptops (or PC tablets and smart phones) or high-speed Internet (or complete lack of and intermittent) at home would experience severe learning challenges, which may delay the acceptance of technology-enabled education [19] and adversely affect their performances. These resources are crucial to obtain HEIs goals and become essential home possessions during emergencies and crises.

The ERT challenges also involve issues of time management, technology literacy, students' assessment, communication, and lack of in-person interaction [3]. For foster effective and meaningful online interaction the educators need to rethink the associated pedagogies, hence support meaningful (higher-order) learning and assessments [20]. Aside from online infrastructure challenges, Bozkurt and Sharma [2] argue for more attention to the lack of empathetic support for students during the crisis because students will remember not the educational content delivered but how they felt during these challenging times. This also presents the importance of motivation and self-esteem protection during an ERT, for resilience and quality learning.

Mulenga and Marbán [21] explore the perspectives of teachers who were engaged in teaching mathematics online during COVID-19 and found that educators and ERT staff need better training and support for using online tools [5]. These challenges give direction to the future, calling for the institution to collaborate with stakeholders to offer better solutions in preparation for future interruptions [2] and formulate more forward-looking strategies towards improving teaching-learning activities during ERT [6]. With the rise in the use of online modalities during COVID-19, it is necessary to assess their effectiveness regarding teaching and learning from different stakeholders [22]. The nature of online learning means that working in partnership with numerous digital innovators and instructors, who see technology as a method of solving problems and reaching new learners, is needed. Accelerated by the COVID-19 pandemic, universities must embrace the new technology while striving to make research-informed decisions in order to find optimal ways to adapt [23]. Several challenges are similar or complementary and might be grouped into more general categories; these groupings may differ depending on one's mental model [24].

There are various methods that could be used to elicit such mental models from participants, such as surveys, questionnaires, and interviews. To this end, this research uses the card sorting method. Cart sorting is a widely used method in Computer Science, particularly in the field of Human-Computer Interaction, to elicit mental models from users [16] in order to organize and structure the content or functionality of interactive systems. However, this useful knowledge elicitation method is very rarely applied in educational settings. We chose to employ card sorting over other potential methods because it is a quick, inexpensive, and reliable method tailored to provide insights into participants' mental models, illuminating the way that they often tacitly group, sort and label tasks and content within their own heads [25], [26]. In our work, card sorting is used to investigate students' mental models of ERT challenges and develop the proposed taxonomy.

In a card sorting session, participants organize topics (cards) into categories that make sense to them, and they may also help in labeling these groups. There are two primary methods of performing card sorts: Open Card Sort (OCS) and Closed Card Sort (CCS) [17], [18], [27]. In an OCS, each participant is given a stack of cards. The participants are then asked to group those cards together in any way they want. Finally, they create labels for the groups that they chose. In a CCS, the researchers create the labels for their respective groups. Participants are given a stack of cards and are asked to put each card into a group. Both methods can be applied in a typical in-person session or by using suitable tools designed to moderate the process remotely [28], [29].

III. METHODOLOGY

A. CARD SORTING

The goal of this paper is to produce a taxonomy of students' challenges in ERT. Thus, we used the OCS method as we do not have any predefined category names. Card sorting data can be analyzed using both qualitative and quantitative methods. We preferred quantitative approaches in this study. Paea et al. [27] and Paea et al. [18] report a typical step-by-step guide to successfully apply these approaches. The next two subsections describe the OCS and how the authors picked the participants of this study.

1) PARTICIPANTS

The target population was first-year students who studied mathematics at a university in the Pacific region during semester 1 (February - June) of 2020. We wanted to understand students' learning needs as new entrants to the university during a pandemic and how best to support them towards persistence or successful completion of mathematics courses. It also provided a more realistic insight into the challenges that mathematics students faced while going through unprecedented changes to teaching and learning during the university's COVID-19 lock-down.

The headquarter campus in Fiji was chosen for implementation purposes because this setting recruits the highest proportion of first-year face-to-face mathematics students. It is also the most central setting considering COVID-19 restrictions on regional travel. The regional university where this research was carried out was shut entirely for 2 weeks before it resumed teaching through emergency remote classes, which continued in this mode for 7 weeks to complete the 14-week semester.

The study recruited a total of 32 (16 males and 16 females) first-year mathematics students who were studying at the university and citizens of the university's country members. The participants' ages ranged from 18 to 28 ($M = 20$ and $SD = 2.9$). The authors' decision to recruit 32 participants as the sample size aligns with the literature recommendation. Two papers [30], [31] address the number of participants needed for card sorting studies. Tullis and Wood [31] recommended that for a card sorting study, the number of participants should be in the range of 20-30 participants. The study by Lantz et al. [30] found that a relatively smaller number ranging from 10-15 participants is needed for card sorting studies.

Participants for this research study were recruited through various means, including personal contacts, referrals and voluntary. The Moodle message, course announcement via Moodle class news and email distribution were used to inform the students about the research and encourage them to volunteer. We also encouraged students to volunteer during our lecture classes. Participants were also recruited using an informal snowball process [32] that was based on researchers' cultural knowledge and skills in recruiting Pacific participants through networking and relationship building [27]. The latter type of recruitment is important for building trust and respect between participants and researchers because Pacific people can willingly partake when they trust the researcher and know their contribution is recognized and valued [27].

2) CARD SORT DATASET

The OCS used 44 cards. These cards represent the challenges, problems, or issues that hinder students' ability to achieve during the unforeseen shift in learning due to the COVID-19. Examples of these card names include "Poor communication and feedback from staff", "Time limitations for quizzes and tests cause frustration", "Clashes between work and

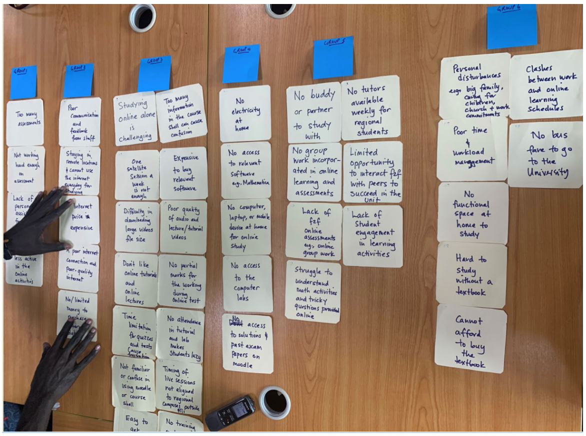

FIGURE 1. OCS participant's pathway in real-time with physical cards.

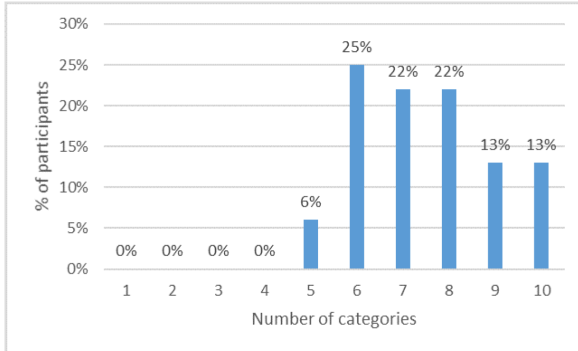

FIGURE 2. Number of categories formed by 32 participants.

online learning schedules'', ''No training on how to do online activities in Moodle'', ''No study buddy or partner to study with'', ''No electricity at home'', ''A poor internet connection and poor-quality internet''.

Prior to the day of the actual card sorting, participants were sent a card sorting demonstration video and an information sheet. This is to provide participants with relevant information about the research objectives and the OCS procedure. The current study used individual card sorting with physical cards and a typical step-by-step road map to effectively apply the OCS method described in Paea et al. [27] and Paea et al. [18]. A stack of 44 cards was placed on the table, and the participants were asked to sort the cards into groups and label these groups. The researchers took a picture of the final card sorting and audio-recorded the verbalized thoughts of each participant.

Fig 1 illustrates participants' pathway through the f2f OCS during an active card sorting performed by one of the participants. In Fig 1, the sorted cards are presented under each blue-coloured paper, which was used by participants also to provide a category name. The category names were numbered for ease of reference.

The actual time of card sorting varied from 20 to 60 minutes for completion. The researchers conducted a t-test for the number of categories grouped by males and females to analyze their respective means. Some participants created just five categories, while others produced more complex classifications involving up to ten categories (M = 7, SD = 1.6). There were no significant differences between the number of categories created by male (M = 7) and female (M = 7) participants. The number of categories created was also unrelated to age (r = 0.23, ns). A total of 239 categories, with a median of 7 categories and a mean of 7 categories, were created by participants, as shown in Fig 2.

B. ONLINE QUESTIONNAIRE DATASET

After analyzing the open card sort data and producing the taxonomy, an online questionnaire was administered to the same 32 participants. The questionnaire included one question that asked participants to measure the importance of the proposed categories taxonomy with a 7-point Likert scale ranging from (1) lowest important to (7) highest important. A participant took about 7-15 minutes to fill in the online questionnaire. The participant's responses were confidential. Table 6 lists the challenges from the most to the least important category taxonomy as rated by the participants.

IV. DATA ANALYSIS METHOD

This paper employs the Best Merge Category Validity Multidimensional Scaling (BM-CV-MDS) algorithm proposed by Paea et al. [18] to analyze the OCS data. The algorithm identifies the mathematically optimal number of categories k, creates and categorizes the initial core categories using the BMM, applies the CV algorithm to categorize the single categories and finally visualizes the clustering results using MDS from the OCS dataset. The algorithm BM-CV-MDS provides valuable insights and an improved taxonomy and its grouping result compared to the existing techniques, such as hierarchical agglomerative cluster analysis (HAC) and K-means. BM-CV-MDS compares favorably to other algorithms, results have shown that it outperforms existing open card sort data analysis methods [18].

A. IDENTIFY THE NUMBER OF CATEGORIES K

First, the BM-CV-MDS algorithm determines the mathematically optimal number of categories k. To this end it applies 6 methods and chooses the k number of categories that was most often found by these methods. The 6 methods used by the BM-CV-MDS algorithm are: a) eigenvalue-one criterion, b) scree plot analysis, c) elbow method, d) gap statistic method, e) silhouette method, and f) 3DCV-average method. The reader is referred to Paea et al. [18] for a detailed overview of these 6 methods.

1) EIGENVALUE-ONE CRITERION

The eigenvalue-one criterion is known as Kraiser [33], is commonly applied to resolve the problem of component numbers. This method retains components whose corresponding eigenvalues are greater than one for interpretation because these components have less variance. Values that are less than one will be discarded. The rationale behind this criterion is that the interpretation of proportions variance smaller than the variance contribution of a single variable are of dubious value. The corresponding eigenvalue can represent the amount of variation in each direction. Katsanos et al. [34] used the eigenvalue-one criterion to identify the optimal number of categories while analyzing OCS datasets. Fig. 3a shows the card sort dataset's eigenvalues, percent of the variance, and cumulative percent of the variance. Fig. 3a displays that only the first seven components have an eigenvalue greater than 1. So based on this proposal, seven factors explaining 68.8% of the total variance are retained for this OCS dataset.

2) SCREE PLOT ANALYSIS

Cattell [35] proposed to look for the points at which the last significant fall or break takes place, in other words, where the line levels off. The logic behind this method is that this point divides the important or major factors from the minor or trivial factors. In Figure 3bi, the inspection of the scree plot and eigenvalues produced a departure from linearity coinciding with a 7-cluster result. Therefore, this Scree Test suggests that the dataset should be examined for 7 clusters. The percentage of variance was also plotted and explained against the number of clusters in Figure 3bii, which indicates that 7 is the optimal number for clusters from this method.

3) ELBOW METHOD

The elbow method is a graphical representation of finding the optimal number of clusters (k) in a dataset. The elbow method calculates the squared difference of different k values. As the k value increases, the average distortion degree becomes smaller. The number of samples contained in each category decreases, and the samples are closer to the center of gravity. As the k value increases, the position where the improvement effect of the distortion degree decreases the most is the k value corresponding to the elbow. It works by finding WCSS (Within-Cluster Sum of Squares), which is the sum of the squared distance between each point and the centroid in a cluster. It calculates the distance of each object to each centroid using the Euclidian Distance. When WCSS is plotted with the k value, the plot looks like an Elbow. As the number of clusters increases, the WCSS value will start to decrease. WCSS value is largest when $k = 1$. When the graph is analyzed it is seen that the graph will rapidly change at a point and thus creating an elbow shape. From this point, the graph moves almost parallel to the x-axis. The k value corresponding to this point is the optimal number of clusters. Fig 4 presents the results of the elbow method for our card sort dataset. A sharp decrease is observed at $k = 4$, which is the optimal number of categories according to this elbow method.

4) GAP STATISTIC METHOD

The Gap statistic is a standard method for determining the number of clusters (k) in a dataset. The Gap statistic standardizes the graph of log(Wk), where Wk is the within-cluster dispersion, by comparing it to its expectation under an appropriate null reference distribution of the data. Fig 5 shows that the optimal number of clusters k is 11 from this Gab statistic method.

TABLE 1. Optimal number of clusters from six methods employed on our open card sort dataset.

Number	Method Name	k-value
1	Eigenvalue-one criterion	7
2	Scree Plot (eigenvalue)	7
	Scree Plot (percentage of variance)	7
3	Elbow method	4
4	Gap Statistic	11
5	Silhouette method	2
6	3D Cluster View (3DCV)-Average method	7

5) SILHOUETTE METHOD

The silhouette method computes silhouette coefficients of each point that measure how much a point is similar to its own cluster compared to other clusters. Fig 6 shows that the optimal number of categories k is 2 in this method.

6) 3DCV-AVERAGE METHOD

The 3D Cluster View (3DCV) algorithm used by Optimal-Sort, a well-known online card sorting tool, simply uses the average (mean) of the number of categories formed by participants in the card sorts. Fig 2 shows that the participants formed a total of 239 categories with a mean of 7 categories. Therefore, from the 3DCV - an average method, the number of categories for this research is 7.

7) SUMMARY - DETERMINE THE OPTIMAL NUMBER OF CATEGORIES K

Table 1 summarizes the number of categories provided by all the aforementioned methods. Based on these results and the BM-CV-MDS algorithm, seven categories are the optimal number of categories for the dataset in this study since this number was selected in most of the employed methods.

B. DENDROGRAM: BEST MERGE METHOD (BMM)

The BM-CV-MDS algorithm used to analyze our OCS data also employs the method described in [17], [18], [27], and [29], the BMM (OptimalSort). BMM is a technique based upon similarity matrices and is considered the industry standard [36]. BMM is a dendrogram tree diagram (DTD) that can be applied to analyze how many participants concurred with parts of this category. The BMM algorithm breaks all categories from all participant responses into groups of their internal pairings. For example, we have three cards, [card$a$, card$b$, card$c$], that obtains paired into [card$a$, card$b$], [card$a$, card$c$] and [card$b$, card$c$]. All pairing groups are scored based on the count of how many times they are obtained in all participant response categories. The algorithm then places them into a queue based on their score. Cards are attached into the DTD by taking card pairing groups from the queue.

(a)

Cluster	Eigenvalues	% of Variance	Cumulative %
1	16.138	36.678	36.678
2	6.2	14.091	50.768
3	2.669	6.065	56.834
4	1.749	3.975	60.808
5	1.325	3.012	63.82
6	1.145	2.603	66.423
7	1.061	2.412	68.834
8	0.981	2.231	71.065
9	0.899	2.044	73.109
10	0.845	1.92	75.028
11	0.759	1.724	76.753
12	0.723	1.644	78.396
13	0.699	1.588	79.984
14	0.67	1.522	81.506
15	0.63	1.432	82.938
16	0.626	1.424	84.362
17	0.592	1.346	85.708
18	0.54	1.227	86.936
19	0.522	1.187	88.123
20	0.48	1.091	89.214
21	0.473	1.075	90.289
22	0.438	0.995	91.284
23	0.401	0.911	92.196
24	0.384	0.872	93.068
25	0.365	0.828	93.896
26	0.355	0.808	94.704
27	0.345	0.784	95.488
28	0.291	0.661	96.148
29	0.261	0.594	96.742
30	0.23	0.522	97.264
31	0.203	0.462	97.726
32	0.18	0.409	98.135
33	0.17	0.387	98.523
34	0.155	0.353	98.876
35	0.126	0.287	99.162
36	0.121	0.274	99.437
37	0.083	0.189	99.626
38	0.065	0.147	99.773
39	0.04	0.091	99.864
40	0.035	0.08	99.943
41	0.021	0.047	99.99
42	0.004	0.008	99.998
43	0.001	0.002	100
44	0	0	100

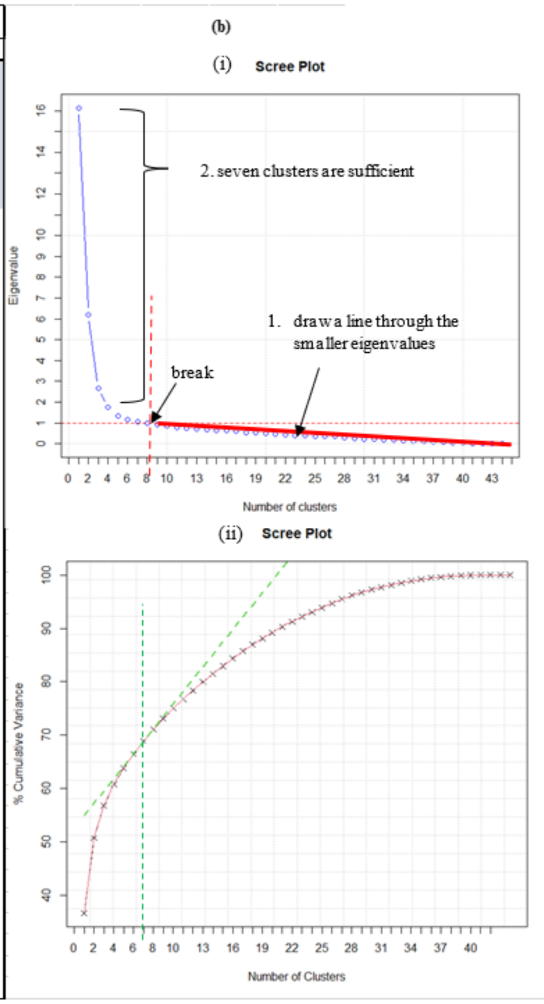

FIGURE 3. Determining the optimal number of categories using eigenvalue-one criterion (a) and scree-plot analysis (b) - bi) The scree plot for the initial variables. bii) The scree plot for the cumulative variance.

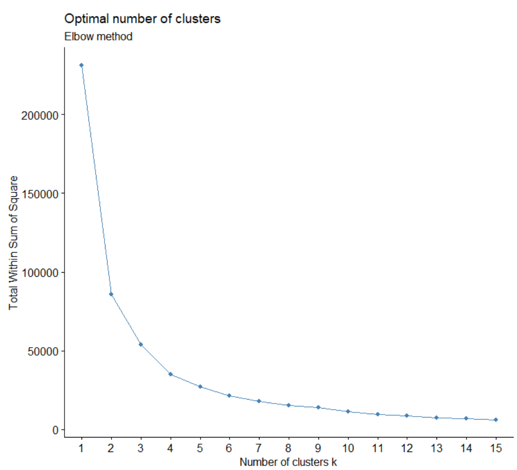

FIGURE 4. Determining the *k* value for OCS dataset using the elbow method.

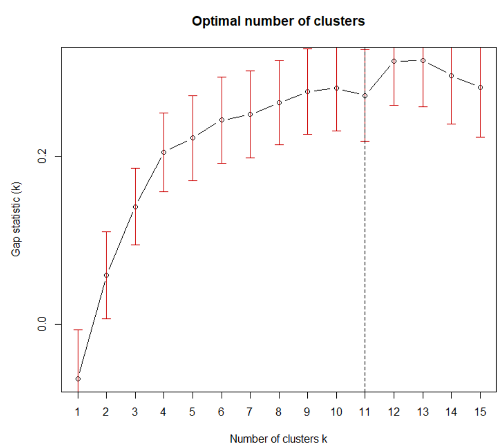

FIGURE 5. Determining the *k* value for OCS dataset using the Gap Statistic method.

If neither card from a pair is in the DTD yet, then the two cards create a new category. If one card from a pair group is already attached in the DTD and the other one is not, then the new card is grouped to the category that contains the other card. If both cards from a pair group are already attached

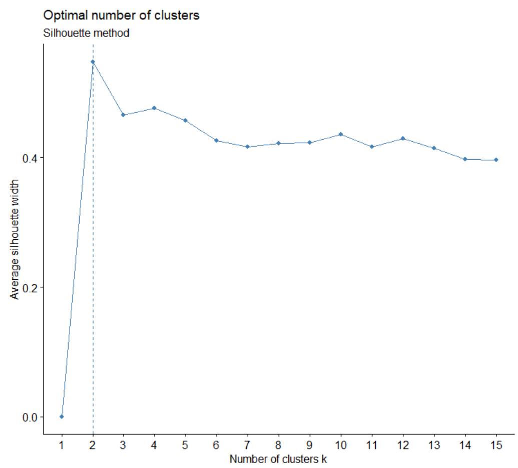

FIGURE 6. Determining the *k* value for OCS dataset using the Silhouette method.

in the DTD but in different categories, then the categories are connected (OptimalSort). Paea et al. [18] delineates the process of BMM.

Fig 7 displays the DTD result constructed for our card sort dataset based on the BMM algorithm. The DTD contained 44 leaves, each leave representing a single card (challenge). The leaves are distanced equally along the vertical axis at 100% participant's agreement. The horizontal axis displays the distance (or dissimilarity measure) at which any two categories are merged. At 0% participant's agreement, all the cards are combined as a single category as shown in Fig 7. The thicker the horizontal lines, the more cards are being added together into a single category.

One major issue that emerges in the quantitative analysis of a card sort dataset is where to locate the threshold line on the DTD. This judgement greatly impacts the final navigation strategy [25]. We applied the 6 methods described in Table 1 to conquer this issue. It was found that for our dataset, a total of 7 categories was appropriated. A threshold of 50% participant's agreement of cards across participants was used to locate the DTD and produce 7 categories (refer to Fig 7). The vertical dash line in Fig 7 indicates the 50% participant's agreement threshold t. This means that 50% of participants placed together at least two cards of each of the 7 categories in Fig 7. This also indicates that 50% of participants created the 18 single-card categories in Fig 7. Again, we employ the BM-CV-MDS algorithm [18] on selecting the threshold t in Fig 7.

Table 2 shows the categories created and the cards grouped under each category from Fig 7. The BMM analysis indicates that for 26 (59.1%) out of 44 cards, 50% of participants or more agreed to place the cards in the similar category. A single card is included only if at least 50% of the participants have determined to group that card in the same category. BMM displays that participants substantially concurred that 18 cards (40.9%) on which the study participants did not meet the threshold of at least 50% participant's agreement or belong to one of the 7 categories.

TABLE 2. Categories and cards grouped under each category when cutting the dendrogram in Fig 7 at 50% agreement (7 categories).

Category	Card Number	Card name (26 cards)
1		4 cards
	C1	*Poor communication and feedback from staff
	C2	*Lack of personal assistance from teaching staff
	C3	*No tutors available weekly for regional students
	C4	*Tutors are less active in the online activities
2		2 cards
	C5	*Typos in lecture notes and examples and solutions having errors cause confusion
	C6	*Lack of mathematics examples from the Pacific context
3		2 cards
	C7	*Time limitations for quizzes and tests cause frustration
	C8	*One satellite session a week is not enough
4		2 cards
	C9	*Not familiar or confuse in using moodle and course shell
	C10	*No training on how to do online activities in moodle
5		4 cards
	C11	*Lack of student engagement in learning activities
	C12	*Limited opportunity to interact f2f with peers to succeed in the unit
	C13	*No study buddy or partner to study with
	C14	*No group work incorporated in online learning and assessments
6		9 cards
	C15	*No electricity at home
	C16	*No computer, laptop, or mobile device at home for online study
	C17	*No functional space at home to study
	C18	*Personal disturbances – e.g., big family, caring for children, church & work commitments
	C19	*Internet price is expensive
	C20	*No/Limited money to purchase internet data
	C21	*No bus fare to go to the University campus
	C22	*Expensive to buy relevant software
	C23	*Cannot afford to buy the textbook
7		3 cards
	C24	*Difficulty in downloading large videos file size
	C25	*A poor internet connection and poor-quality internet
	C26	*Staying in remote locations & cannot use the internet every time for studying

TABLE 3. Cards on which the study participants did not attain the 50% agreement or higher threshold.

Card number	Single Card Name	SCTPA%
C27	*Studying online alone is challenging	704
C28	*Hard to study without a textbook	689
C29	*Struggle to understand math activities and tricky tutorial questions provided online	670
C30	*Too many Information in the course shell can cause confusion	669
C31	*Timing of live sessions not aligned to regional campuses outside Fiji	637
C32	*No access to the computer labs	631
C33	*Don't access to solutions & past exam papers on moodle	629
C34	*Lack of f2f online assessments e.g., online group work	621
C35	*Clashes between work and online learning schedules	620
C36	*Too many assessments	619
C37	*No partial marks for the working during online test	612
C38	*No access to relevant software e.g., Mathematica	606
C39	*Poor time & workload management	605
C40	*Don't like online tutorials and online lectures	592
C41	*No attendance in tutorial and lab makes students lazy	584
C42	*Poor quality of audio and lecture/tutorial videos	547
C43	*Not working hard enough on assessment	541
C44	*Easy to get solutions to quizzes and tests on the Internet	503

These 18 cards are listed in Table 3. Even though these single cards will be grouped at a later stage by BMM, it is highly probable that these card names might have puzzled

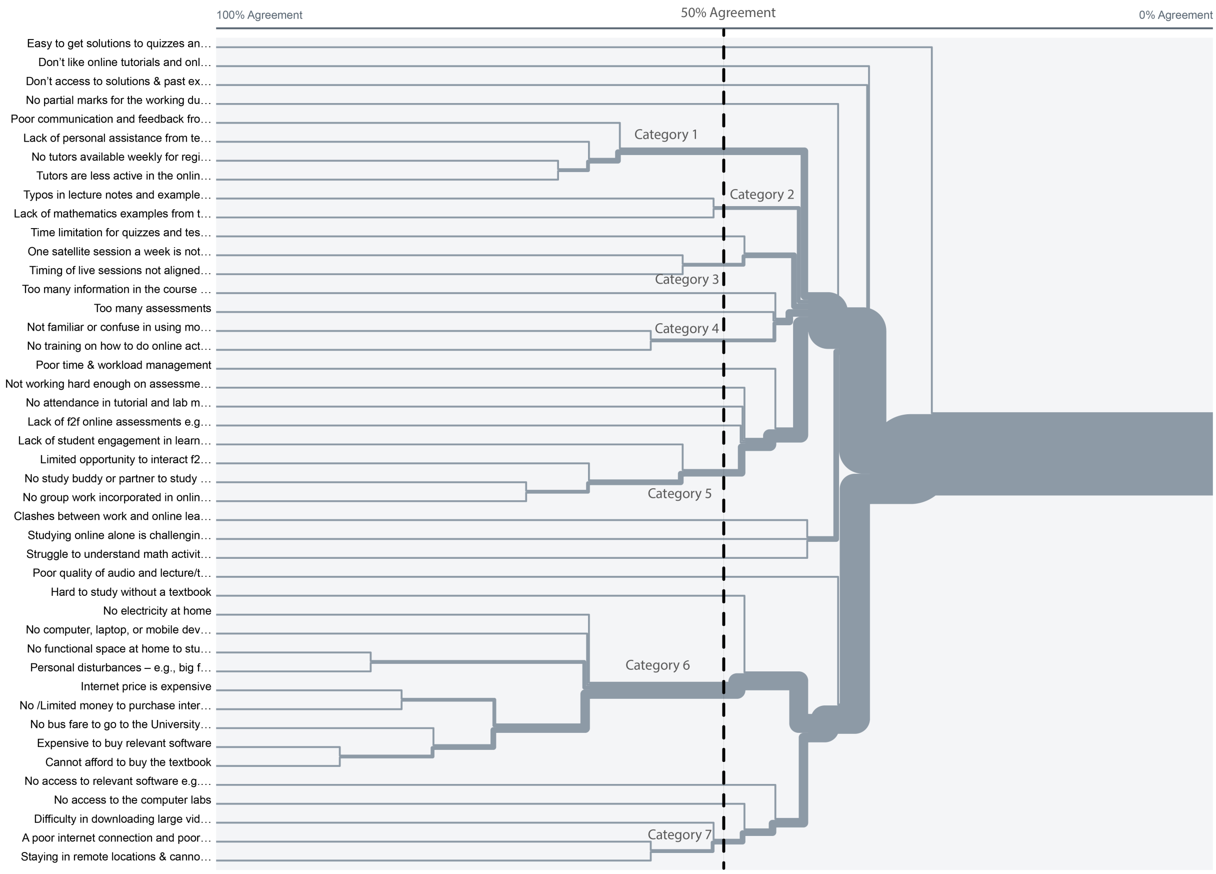

FIGURE 7. **BMM dendrogram tree diagram from our dataset involving 32 participants.**

our participants and need careful scrutiny. The smaller the BMM threshold % agreement indicates the confusion in participant's thinking. Prior to applying the category validity technique (CVT) to group all the single cards in Table 3 into one of the 7 categories in Table 2 we need to calculate the Single Card Total Participant's Agreement (SCTPA) percent (see next subsection).

C. CATEGORY VALIDITY TECHNIQUE (CVT)

There are two main parts in this section. First, the BM-CV-MDS algorithm [18] calculates the SCTPA score, and second, it calculates the CVT score.

1) PART 1: SINGLE CARD TOTAL PARTICIPANT'S AGREEMENT (SCTPA) SCORE

SCTPA for each card is calculated using the following formula:

$$SCTPA(k) = \sum_{i \neq k}^{n} C_{k,j},$$

where $SCTPA(k)$ is the single card total participant's agreement score. The algorithm sums up all the cells of the given k row (except the cell value $C(k, k)$) on the similarity matrix from Fig 8. The algorithm then arranges the single cards in descending order based on the STCPA %. The higher the SCTPA %, the more similar that single card is to others. This suggests that more participants paired this card with others more often. The arrangement of Table 3 is preparing the single cards for grouping using the CVT. The algorithm picks the card with the highest percent of SCTPA (C27) to group first. The procedure continues up to the last single card C44. If two cards have equal percentages, the algorithm will select the card close to the top of the similarity matrix (see Fig 8). The reason is that the strongest pair is located in the top left corner, grouping them with the next related strongest pair that either of those cards have, and then the procedure is repeated for that new pair. This way, categories of cards that are strongly related to each other seem together in the same shade of blue region on the similarity matrix. An example is provided to help explain the calculation better. Refer to single card number C27 of Table 3 "Studying online alone is challenging" and the red cells of Fig 8.

$$\begin{aligned} SCTPA(C27) &= \sum_{i \neq k}^{n=43} C_{k,j} = C_{34,1} + C_{34,2} + C_{34,3} + \ldots \\ &\quad + C_{34,41} + C_{34,42} + C_{34,43} \\ &= 6 + 3 + 3 + \ldots + 3 + 15 + 40 \\ &= 704 \end{aligned}$$

2) CVT SCORE

CVT is a technique based upon similarity matrices [18]. The similarity matrix is utilized to explain how strong is the relation between cards. In our case, the similarity between two cards measures how often the participants grouped them together. For example, the first column of the similarity matrix displays that 87% of participants put the challenges "expensive to buy relevant software" and "cannot afford to buy the textbooks" in the same group, meaning that these two cards are interconnected. Looking further down the same column, "expensive to buy relevant software" and "not working hard enough on assessment" shows 0%, meaning that no participants placed these two challenges together.

CVT is employed to calculate the final categories of the single cards in Table 3 by grouping the single cards into one of the initial categories identified in the BMM result (Table 2). To group the single cards in Table 3, their category validity score (CVS) with respect to each of the initial categories was calculated using the following formula:

$$CVS(k \subset A) = \frac{\sum_{i \neq k}^{I \subset A} C_{k,i}}{n \sum_{i \neq k}^{I \subset M} C_{k,i}},$$

where $CVS(k)$ is the category validity of a particular card k, n is the number of cards in the category A including the newly added cards, $I \subset M$ represents all the cards, excluding k in the M category, and $I \subset A$ is the entire cards that belong to the similar A category of k, excluding k itself. The algorithm, therefore, sums all the cells of a given k row (except the diagonal value $c(k, k)$), all the cells of the cards which belong to the same category of k (except, again, the diagonal value $c(k, k)$), then divides the latter value with the former. The algorithm compares the CVS and groups the single card in a category that has the highest CVS. The algorithm uses as its first card the one with the highest SCTPA shown in Table 3 and repeats the process until all single cards belong to a category.

An example is given to illustrate the algorithm's steps. For instance, let's assume that the algorithm is trying to find a category for single card C27 ("Studying online alone is challenging") in Table 3. The algorithm calculates the CVS for single card C27 in each of the 7 categories shown in Table 2. In the following, an example of the calculation of the CVS for single card C27 for category 1 is presented (see Table 2 and the black circular region of Fig 8).

$$\sum_{i \neq 34}^{I \subset A} C_{34,j} = C_{34,25} + C_{34,26} + C_{34,27} + C_{34,28}$$
$$= 3 + 0 + 9 + 0 = 12,$$
$$\sum_{i \neq 34}^{I \subset M} C_{34,j} = C_{34,1} + C_{34,2} + C_{34,3} + C_{34,4}$$
$$+ \ldots + C_{34,41} + C_{34,42} + C_{34,43} = 704,$$

and $n = 5$.

$$\text{Then, CVS } (34 \subset A) = \frac{\sum_{i \neq 34}^{I \subset A} C_{34,i}}{n \sum_{i \neq 34}^{I \subset M} C_{34,i}} = \frac{12}{5(704)} = 0.0034$$

TABLE 4. Single card 1 CVS scores in 7 categories.

Category	CVS	Category	CVS
1	$\frac{12}{5(704)} = 0.00341$	5	$\frac{130}{5(704)} = 0.03693$
2	$\frac{18}{3(704)} = 0.00852$	6	$\frac{66}{10(704)} = 0.00938$
3	$\frac{30}{3(704)} = 0.01420$	7	$\frac{36}{4(704)} = 0.01278$
4	$\frac{29}{3(704)} = 0.01373$		

The CVS score of single card C27 in category 1 is therefore 0.0034. The algorithm repeats the calculation of single card C27 for all the other six categories, and the results are displayed in Table 4. Table 4 shows that category 5 has the highest CVS of 0.03693. Therefore the algorithm placed the single card C27 in category 5. The same process is repeated to the rest of the single cards in Table 3. The final categories and their cards are shown in Table 5.

Table 5 demonstrates the final category results in five columns, where the first column describes the primary level category number. The second column displays the similar category labels, based on the highest number of category labels selected by participants. These category labels identify the most repeated similarities amongst all participants' data, which can be considered as the primary level contents to appear on the derived taxonomy. For instance, Category 4 of Table 5 indicates that 100% of participants label primary level "Need more training on how to use moodle", 100% of participants label it "Challenges in using moodle", 80% label it "Moodle issues", and 75% label it "Difficulties with using moodle". This result suggests that "Need more training on how to use moodle" or "Challenges in using moodle" can be the proposed label for the primary level Category 4 as identified by the list of similar associated cards shown in the fifth column. A comparable procedure can be repeated for the remaining of the proposed category labels in Table 5. Hence, the second and third highest similar category labels are also essential representations of participants' card similarities.

The third column suggests the popularity score of each category. The total number of cards was counted from the category that each and every participant groups into a category, then divided by multiplying the total number of cards in that category with the total number of participants. The higher the category score, the more popular the category is. This is significant when deciding ties where two categories may have similar labels (category) (%). The most popular category could then be adopted as the best category name for that particular cluster of cards. The fourth column is the proposed

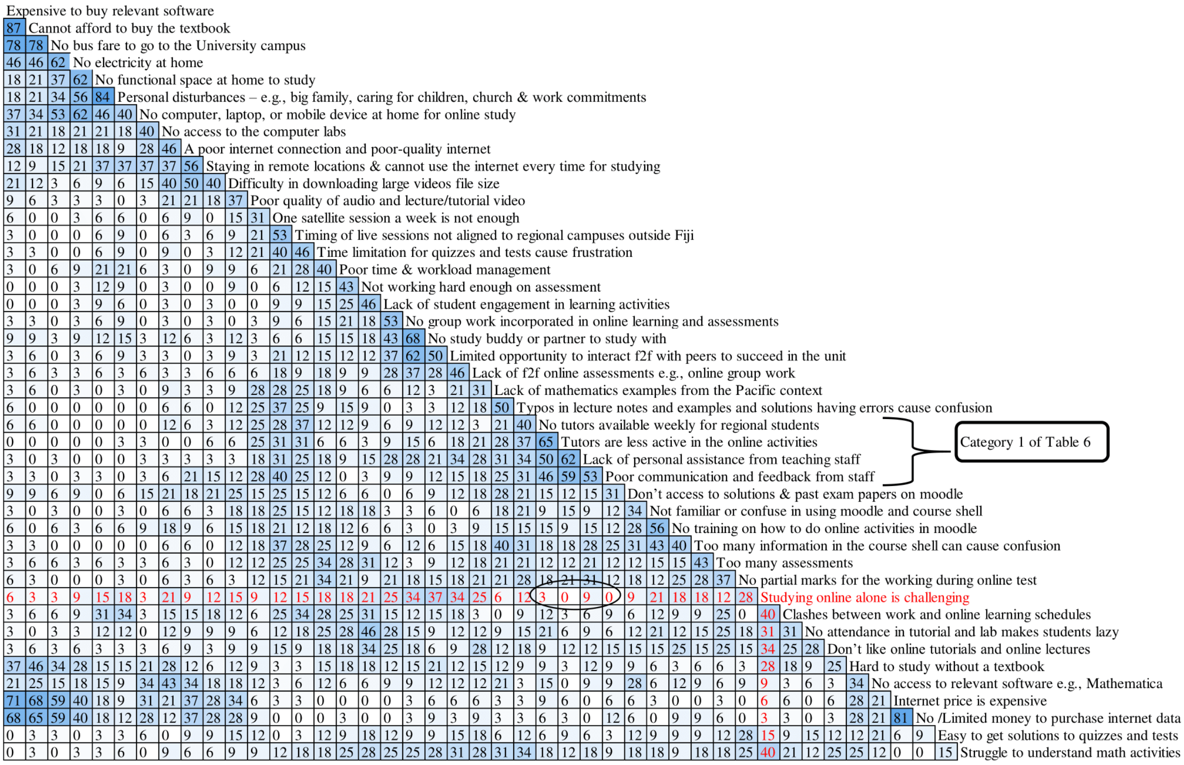

FIGURE 8. Similarity matrix displayings how many participants agree with each pair combination of cards.

category and the list of challenges (cards) is presented in the final column. To ensure usability and simplicity for better comprehension of participants' challenges categories, we follow the steps described in Spencer [16] by using standardized labels. Participants often use very similar, but not identical words to create category labels. It is hard to see any patterns when there are tiny differences getting in the way. For instance, the row for Category 6 in Table 5 shows that 92% of participants label the category as ''Financial issues'', 75% label it ''Financial difficulties'', and 75% label it ''Personal problem faced by students''. This result proposes that ''financial hardship'' can be the proposed standardized category label for primary level Category 6 as identified by the list of similar related category labels and similar related card challenges displayed in the fifth column. A similar application can be repeated for the rest of the proposed group labels in Table 5. This process of co-constructing meaning between participants and the researcher(s) is sought in the Pacific way of carrying out card sorting research [27].

3) MULTIDIMENSIONAL SCALING (MDS) VISUALIZATION

MDS is a method for visualizing the level of similarity of individual objects in a dataset, where the distance is known between pairs of objects. Data visualization is the art and science of presenting data in a clear and engaging way. Fig 9 displays the relationships between card of challenges in a multidimensional space plot. The MDS algorithm used to analyze our OCS data also employs the method described in [17] and [29].

D. PARTICIPANT'S RESPONSES TO THE QUESTIONNAIRE

Table 6 shows how the participants rated the importance of the 7 categories in the proposed taxonomy that were produced based on analysis of the OCS data. This rating on a scale from 1 to 7 expresses how much the participants found that each challenge affected their studies during the sudden shift from f2f to ERT because of COVID-19. Financial hardship appears to be the most impactful challenge, and the challenge regarding online course delivery appears to have the least perceived impact.

V. FINAL CATEGORIES TAXONOMY DISCUSSION

This paper presents a taxonomy of learning challenges faced by first-year mathematics students due to the unexpected shift from f2f to ERT during the COVID-19 pandemic. This section discusses the seven proposed categories taxonomy of challenges identified (see Table 5) against the recent findings from the literature. Online learning success during ERT was highly reliant on numerous integrated components, such as students, educators, learning resources, and the technology used.

A. FINANCIAL HARDSHIP

The financial hardship category is the major challenge most participants faced during the COVID-19 lock-down, as indicated in the participant's respective ratings of challenges

TABLE 5. Proposed categories taxonomy for card sorting dataset after running the CVT of all single cards.

Category Number	Similar Category Label (%)	Popularity Score (%)	Proposed Category Taxonomy Label	Card Number
Category 1	· Teaching staff delivery issues (83) · Tutor delivery problem (80) · Poor response from staff (67) · Teaching staff issues (67)	· Teaching staff delivery issues (5) · Tutor delivery problem (4) · Poor response from staff (4) · Teaching staff issues (4)	Lack of online learning support	C1, C2, C3, C4, C42
Category 2	· Content issues (67) · Tutor shortfall (50) · Teaching team failure (50) · Teaching materials delivery (50)	· Content issues (2) · Tutor shortfall (2) · Teaching team failure (2) · Teaching materials delivery (2)	Problem with online course delivery	C5, C6
Category 3	· Online course issues (62) · Student excuses (60) · Time limitations (56) · Challenges faced by students (50)	· Online course issues (10) · Student excuses (6) · Time limitations (5) · Challenges faced by students (5)	Time and workload management	C7, C8, C31, C35, C36, C39, C41, C43
Category 4	· Need more training on how to use moodle (100) · Challenges in using moodle (100) · Moodle issues (80) · Difficulties with using moodle (75)	· Need more training on how to use moodle (4) · Challenges in using moodle (4) · Moodle issues (6) · Difficulties with using moodle (3)	Learning management system issues	C9, C10, C30, C33
Category 5	· Online activities (64) · Challenges in studying alone (60) · Online learning issues (58) · Challenges in learning online (53)	· Online activities (7) · Challenges in studying alone (6) · Online learning issues (7) · Challenges in learning online (9)	Lack of f2f interaction	C11, C12, C13, C14, C27, C29, C34, C37, C40, C44
Category 6	· Financial issues (92) · Financial difficulties (75) · Personal problem faced by students (75) · Resources challenges (64)	· Financial issues (24) · Financial difficulties (15) · Personal problem face by students (12) · Resources challenges (11)	Financial Hardship	C15, C16, C17, C18, C19, C20, C21, C22, C23, C28, C32, C38
Category 7	· Internet challenges (40) · Resources accessibility (33) · Internet issues (29) · Poor internet connection (29)	· Internet challenges (5) · Resources accessibility (2) · Internet issues (5) · Poor internet connection (2)	Internet challenge	C24, C25, C26

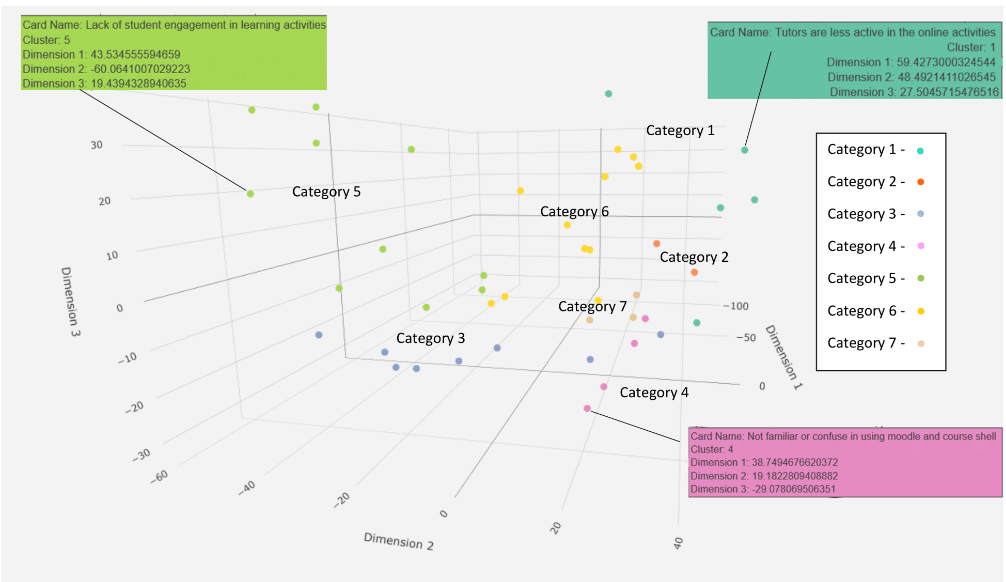

FIGURE 9. Multidimensional scaling of the clustering results from Table 5.

perceived importance (M = 6.62 and SD = 0.75; see Table 6). As reported, domestic workers have suffered from job loss and/or a drop in working hours as one of the negative impacts of COVID-19 [37]. The issues of parental unemployment and job displacement during COVID-19 have put many families worldwide in financial crisis, making it very difficult for them to take care of everyday needs, including education [38]. Factors related to experiencing financial difficulties more

TABLE 6. Descriptive statistics regarding participants' perceived ratings (1 = lowest important, 7 = highest important) of the importance of the seven categories of learning challenges in ERT.

Proposed Category Taxonomy Label	Mean	Standard Deviation
Financial Hardship	6.62	0.75
Lack of f2f interaction	5.25	0.88
Time and workload management	4.88	1.13
Lack of online learning support	3.99	1.52
Learning management system issues	2.81	1.18
Internet challenge	2.78	1.98
Problem with online course delivery	1.75	0.92

often among university students were being female and older, having a migration background and having children, and being enrolled in a Bachelor's compared to a Master's degree program [39]. Students depend on part-time jobs to support and finance their needs, and those who lost their jobs due to the crisis lock-down might experience financial hardship. Students who were financially supported by their parents and guardians might not or only partly continue to receive financial support, as in the challenge of the crisis. The parents might encounter difficulties in a worsened income situation themselves [38], [40]. Studies describe that financial uncertainty puts many students in a demanding and stressful position, which, in turn, affects their mental well-being [41], [42]. For instance, due to the COVID-19 lock-down, students were required to study from home during the time of social distancing and lock-down. The challenges like "no electricity at home", "no functional space at home to study", and "personal disturbances - e.g., big family, caring for children, church & work commitments" reveal that studying from home during an emergency or crisis would be much more difficult for students who live in villages, extended families and crowded houses without any study-friendly environment [43]. This is common with Pacific students and families from rural and low socio-economic backgrounds. Therefore the impact of financial hardship can cause the absence of students from online studies and activities, adversely affecting their academic performance and program completion.

B. LACK OF F2F INTERACTION

The transition from an environment of conventional education to distance and virtual learning could not happen overnight. This speedy transformation is linked to several difficulties and challenges at this point [44]. The Lack of F2F Interaction category is the second major challenge most participants faced during the COVID-19 lock-down (M = 5.25 and SD = 0.88; see Table 6). There is broad agreement that teachers play a key role in providing high-quality learning opportunities to students and fostering students' learning [45]. Most HEI in the Pacific region rely heavily on f2f mode for sharing and distributing knowledge, hence, the capacity of the institution to handle the circumstances of an unprecedented ERT can be a real challenge. The online learning can be successful in developed and digitally advanced countries [46], which is why in the Pacific, it is ineffective, especially in studying Mathematics. Online classes cannot be of interest to those students who are in favour of tactile and physical learning. Conventional classroom socialization is another significant lack of activity and interest in online learning. Studies suggest students hardly see fellow students in person and only communicate with their fellows digitally, and thus the real-time sharing of ideas, knowledge and information is partially missing from the digital learning world [47], [48]. However, at the same time students are being exposed to more autonomy. The majority of participants believe that a lack of f2f learning interactions and assessment strategies can make things hard for them to succeed during the ERT. For instance, some participants mentioned the lack of face-to-face interaction with peers and that there was no study buddy or partner to study with.

C. TIME AND WORKLOAD MANAGEMENT

The time and workload management category taxonomy is the third major challenge most participants faced during the COVID-19 lock-down (M = 4.88 and SD = 1.13; see Table 6). Effective time management requires organizing, planning, scheduling, and managing one's study time to complete everything students had planned. Michinov et al. [49] highlighted the significant function of time management as a critical success factor of online learning. On the other hand, inefficient time management causes problems and leads to procrastination, which is negatively correlated with performance.

A student's workload can be of various types, from simply having too many activities to do in insufficient time [50], to the degree to which time pressures and work demands outweigh in the professional environment [51]. Student workload is not a one-dimensional space phenomenon, rather it is constructed of physical demand, mental demand, temporal demand, effort, consistency, performance, and frustration processes. The online workload should be thoroughly creative and designed by considering all multi-dimensions [52]. Studying from home normally requires enormous self-discipline and motivation to follow through with online lessons [8], [43], especially in the earlier time when students are getting used to the new system, which might overwhelm them.

In addition, lecturers' unfamiliarity and incompetency with the new mode of delivery could overwhelm students by putting too many study materials and assignments which would add to the demotivation that students might feel towards the course [53]. In the current study, the list of challenges that participants considered under this category highlights the importance of putting an effective learning support system related to participants' time and workload management in place during a pandemic crisis. For instance, the time limitations for quizzes and tests, the timing of live sessions is not aligned to regional campuses outside Fiji, too many assessments, poor time and workload management and no attendance in tutorial and lab sessions make students disinterested.

D. LACK OF ONLINE LEARNING SUPPORT

The lack of online learning support category taxonomy is the fourth major challenge most participants faced during the COVID-19 lock-down (M = 3.99 and SD = 1.52; see Table 6). Participants were concerned with the lack of support from teaching staff during the ERT, which can be linked to the delivery mode's remote nature. This includes little time for interpersonal relationship development, lack of training and support, lack of incentives to design and deliver the online course, poor communication, and being less active in online activities [54]. The educators and lecturers have not been prepared up to standard to teach well with technology, let alone teach and communicate remotely with technology. Hence, they struggled to understand how to figure out the use of digital tools, online resources, and apps to continue and communicate their teaching online [55]. Challenges in this category include poor communication and feedback from staff, lack of personal assistance from teaching staff, lack of the availability of tutors for regional students and poor quality of audio and lecture/tutorial videos.

Crawley et al., [56] mention that many educators and lecturers have difficulty with the delivery of the course materials and engaging their students due to insufficient visual and face-to-face interaction with their students, thus feeling excluded and having less control over how to adjust and communicate their classes. In addition, many educators and lecturers who teach face-to-face classes are not interested or concerned in teaching online classes [57], [58]. One of the major concerns is that these educators and lecturers have been teaching face-to-face classes for years and do not believe and feel comfortable changing to the online delivery technique. This discomfort is the fear of the unknown, or it may be associated with the lack of ability to connect with students within the online environment. Following fear of the unknown, many educators are worried that computers would replace them [58], [59].

E. LEARNING MANAGEMENT SYSTEM (LMS) ISSUES

The LMS issues category taxonomy is the fifth major challenge most participants faced during the COVID-19 lock-down (M = 2.81 and SD = 1.88; see Table 6). As reported, the challenges under this category taxonomy (i.e., "Not familiar or confuse in using moodle and course shell", "No training on how to do online activities in moodle", "Too many information in the course shell can cause confusion" and "Don't access to solutions & past exam papers on moodle") showcase the problems faced with the Moodle platform. Mpungose [59] explores lecturers' reflections on using the Moodle platform to teach first-year students. The study discovered that even though the university policy made the use of Moodle platform compulsory, lecturers had difficulties producing and sustaining a smooth teaching and learning process since most students struggled to use the Moodle platform. Mpungose [59] discovered that students enjoyed using the Moodle platform to download the readings and module outlines and do quizzes. However, the study revealed that students were upset with Moodle platform because they did not find the discussion forums and chat rooms to be user-friendly.

Most participants in our study also believed that poor audio and lecture/tutorial videos and too much information in the course shells can cause confusion. The challenge of writing mathematics online using Moodle features is still huge, and alternatives such as uploading snapshots of write-ups are also not feasible keeping in mind the intermittent internet facilities and costly mobile data in specific regions, such as the South Pacific. Many educators have no previous experience or knowledge in online teaching. Although they received numerous forms of guidance and training during the pandemic, the long-term effects of such guidance and training remain arguably minimal. The Moodle platform would be expected to be a friendly learning environment for students, and for course instructors to develop, disseminate learning materials, and share knowledge through multiple online activities such as forums and chats [2].

F. INTERNET CHALLENGE

The internet challenge category taxonomy is the sixth major challenge most participants faced during the COVID-19 lock-down (M = 2.78 and SD = 1.98; see Table 6). Online learning is described as the experience and skill of transferring knowledge through various media platforms using video, audio, images, text communication, software [46] and internet networks [60]. Internet access is one of the primary challenges and problems of online learning in specific regions, such as the Pacific. In the Pacific Island countries and especially the remote communities, online learning (as well as blended learning) is mostly problematic due to the absence of access to fast, affordable and reliable internet connections [61] and even the lack and cost of electricity. These hinder the delivery of online learning, mainly for those students who are staying in rural areas as well as marginalized communities [53], [62]. Students who access the internet through smartphones are sometimes helpless to take advantage of online learning because a vital amount of online content is not accessible through smartphones. Some learners face internet connectivity problems, accessing classes, and downloading course materials [63], especially the low-income families, who may have occasional internet access or a rather unstable connection. The poor and intermittent internet connection created the challenges in this category such as "difficulty in downloading large videos file size", "a poor internet connection and poor-quality internet" and "staying in remote locations & cannot use the internet every time for studying".

G. PROBLEM WITH ONLINE COURSE DELIVERY

The problem with online course delivery category taxonomy is the seventh major challenge the participants faced during

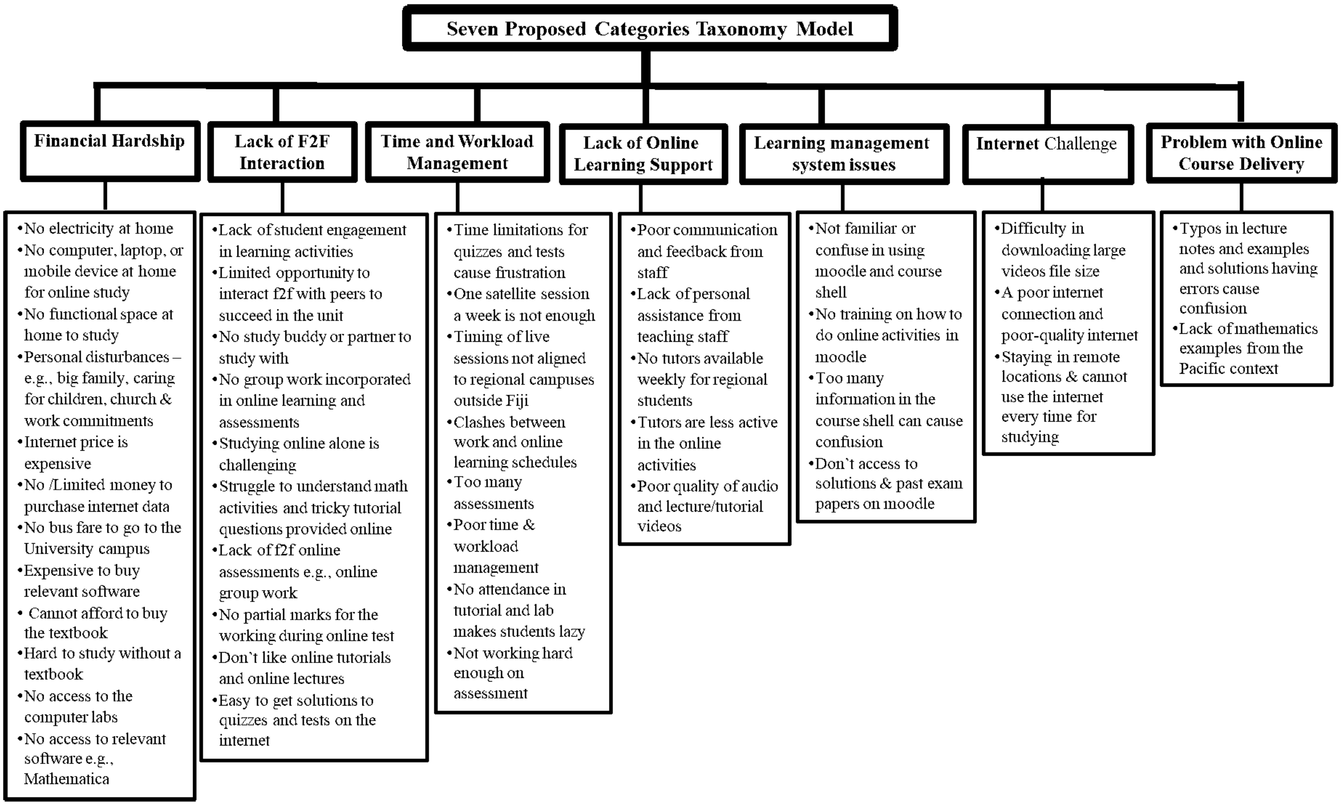

FIGURE 10. Seven proposed categories taxonomy model and challenge cards.

the COVID-19 lock-down (M = 1.75 and SD = 0.92; see Table 6). Mathematics teaching and learning requires an efficient, skilled and effective pedagogical methodology and design to incorporate online teaching and learning environments during a crisis. This will also be valuable as tertiary education subsequently pivots to include more digital components in its delivery.

The successful outcome of online learning is highly dependent on numerous integrated factors, such as students, educators, learning resources, and the technology used [64]. Researchers have also found several potential disadvantages of online learning, such as teacher shortfall, content issues, problems with teaching material delivery, lack of student discipline, lack of internet access, and lack of social interaction. The latter are common challenges for educational organizations and stakeholders [13]. For instance, "typos in lecture notes and examples and solutions having errors cause confusion" is one of the challenges in this category.

The COVID-19 epidemic has forced and affected many students to transfer to online learning or distance learning, an unfavourable adjustment for many who are associated with face-to-face classes. Technical problems might happen in an online-only environment due to many factors. This may sound obvious but technical problems and the internet connection issues add to the online environment's frustration and interfere with the online learning classes. Sometimes a student's computer would shut down unexpectedly, there are moments when their Wi-Fi is spotty, and small-sized screen monitors can make it tough to keep up with virtual classmates and the learning environment.

VI. SEVEN PROPOSED CATEGORIES TAXONOMY MODEL IMPLICATIONS

The seven proposed categories in our taxonomy give direction to the types of support that are relevant for addressing issues as a basis for participants' success in the sudden shift to ERT during an emergency and crisis, such as the COVID-19 pandemic. Fig 10 presents the seven proposed categories taxonomy model. While this new model governs the proposed taxonomy for students studying mathematics, we argue that it might be equally relevant to other disciplines.

Looking at these proposed categories of challenges from an affirmative perspective means that the institution's level of preparedness during the ERT must be strengthened. In the second lock-down in Fiji, we can say that the level of preparedness by the university was better than during the first lock-down in 2020. The arrangement for the online Zoom link was more efficient than before. University had organized additional activities to support students, including offering offline print packs, scholarships to students with specific characteristics, and loans of university equipment (laptops etc.). However, in terms of "financial hardship", the institution must be ready to compensate students' Internet and technological needs in an emergency. This study emphasizes the need to improve the affordability and availability of free access to learning resources during a pandemic. Fig 10 demonstrates a learning support model designed from the insights of the findings of this research.

The model suggests that the appropriate way to support first-year Pacific mathematics students learning challenges during any crisis or emergency must be understood from the dynamic interplay between their finances, time and workload management, online learning literacies, f2f interpersonal interaction, course delivery, internet access, and lack of support within a given socio-cultural learning context. This leads to the understanding that participants' learning challenges during ERT are made up of different related parts that must be understood within the socio-cultural context in which they are understood and experienced. As demonstrated by the heptagon of Figure 9, participants' challenges can be appropriately addressed in a more interconnected and multidimensional system. It means that people within the respective context, whether at home or in HEI, should be the catalyst for change and the driver of students' success during the pandemic crisis and emergencies.

VII. CONCLUSION

This paper presents a study exploring the challenges faced by first-year mathematics students in the Pacific region during the ERT dictated by the COVID-19 pandemic. To this end, we employed the open card sorting method to produce a taxonomy of such challenges. First, a total of 32 first-year mathematics students produced groupings of 44 cards representing challenges, problems, or issues related to ERT during COVID-19. Next, we used the recently proposed BM-CV-MDS algorithm to quantitatively analyze the collected open card sort data. BM-CV-MDS works by first identifying the optimal number of categories from six methods employed, then it creates the initial core categories using the Best Merge Method, then it applies the Category Validity Technique to categorize the rest of the cards, and finally it visualizes the clustering results using Multidimensional Scaling.

The main contribution of this paper is the development of a new taxonomy of challenges for first-year Pacific mathematics students. Such a taxonomy is valuable, especially in designing and evaluating ERT approaches for learning mathematics during a crisis. Previous work has contributed various sets of challenges and heuristics for the field of education. However, to the best of our knowledge, the use of card sorting combined with a new algorithm to analyze the collected data is done for the first time in order to explore this topic. This is an other contribution of this paper. Our study highlights the significance of using card sorting as a new method in the field of educational research to understand students' mental models on various topics. In our case, the topic was the learning challenges faced by students in ERT. Such a deeper understanding of these challenges can greatly help education stakeholders to design a more student-oriented learning support model for emergencies and crises. From a wider perspective, the methodology we used has a good scope in the field of educational research and can be utilized in a number of areas, such as the design of online courses and other contextualized learning resources and support models.

The findings from this study highlight the need for more in-depth future research on the proposed taxonomy of challenges using qualitative data to provide deep and rich insights into card-sorting findings. This can be done using the Pacific research approaches, such as "talanoa" (talking) [27] to provide rich and deep meanings to the research topic. Studies such as this can also explore and evaluate each challenge's main causes and discover measures from students' own perceptions and experiences. This would provide better information to the institution on the types of learning support systems that must be implemented in a given emergency and crisis. An extension of the research setting to the wider Pacific region would enhance understanding of the topic from the dynamic nature of the Pacific cultural diversity.

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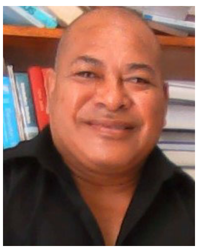

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