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Can I have a Mooc2Go, please? On the Viability of Mobile vs. Stationary Learning

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Abstract. The use of mobile technology has become an ubiquitous part of our daily lives and enables us to perform tasks on-the-go and anytime that once were possible only on stationary devices. This shift has also affected the way we learn. The use of mobile devices for learning on-the-go requires users to multitask and divide attention between several activities, at least one of which (the learning activitiy) with high cognitive load. Massive Open Online Courses (MOOCs) have become a popular way for people around the world to learn outside of the traditional and formal classroom setting. While most MOOC platforms today offer specific apps to learn via mobile devices, the learning situation and its effect on learners while using mobile devices on-the-go has not been studied in full. In contrast to most existing mobile learning studies which were conducted in the lab, we focus on real-life situations commonly experienced by learners while they learn on-the-go. In a study with 36 participants and four mini-MOOCs deployed on edX, we investigate the differences in MOOC learners' performance and interactions in two different learning situations with mobile devices (stationary learning and learning on-the-go) and under two environmental variables (daylight and crowdedness).

Keywords: Mobile Learning · MOOCs · Divided Attention

1 Introduction

With the rapid advancement of mobile technology, the use of mobile devices has become ubiquitous around the world—about 98% of the population in developed countries, and 50% of the population in developing countries had mobile-broadband subscriptions in 2017 [19]. This development has affected the way people exploit mobile technology to learn new skills—a significant number of people use mobile devices for learning. A 2012 survey on lifelong learning by Tabuenca et al. [24] found that 56% of learners used their smartphone on a daily basis, whilst a study on mobile language learning by Dingler et al. [6] in 2017 reported that about 38% of learning sessions took place while in transit. According to O'Malley et al. [15], mobile learning refers to *"any sort of learning* *that happens when the learner is not at a fixed, predetermined location, or learning that happens when the learner takes advantage of the learning opportunities offered by mobile technologies."*

The start of the MOOC movement in 2011 vastly widened the learning opportunities for people across the world outside of a formal education setting. While in the early years MOOC platforms lacked support for mobile devices, by 2015, most well-known platforms (such as edX, Coursera and Udacity) offered a mobile learning experience [13], either in the form of responsive web pages or native mobile apps (for Android and iOS), thus further expanding the possibilities to learn anywhere and anytime.

Critical for mobile learning [22, 20, 17, 21] is the *learning situation*—a set of environmental and intentional constraints [2]—in which learning occurs. A learner's available time, the employed device type(s), and the frequency of interventions or distractions are only a few of those constraints that affect learning. One common learning situation for MOOC learners is *stationary learning*: here, learners use a device with a large screen to access course materials whilst being stationary in a comfortable environment (e.g. at their desk), enabling them to focus on the learning activity. In the mobile learning situation[3], the conditions are quite different—mobile devices have considerably smaller screens and they are used in various and possibly changing environments which require learners to multitask (e.g., learning whilst walking or transiting). In terms of learning, this situation results in an increase in interruptions and distractions [20], an increase in cognitive load [24, 3, 6], and increased frustration [5].

Existing works on mobile learning in MOOCs focus on the design and delivery of course content for mobile devices [18, 13] as well as the learning experience on mobile devices [16, 25, 5, 25]; the latter though is typically studied *in the lab*, instead of real (urban) environments. Thus, little is known about how multitasking and a multitude of overlapping *real-life conditions* affect MOOC learning on-the-go compared to stationary learning. This knowledge gap serves as the core motivation for our work.

More specifically, we focus on the impact of the learning situation on learners' performance and interactions, the effect of different environmental variables on the learning on-the-go process, and the correlation between learners' perceived workload and their performance/interactions. We analyzed the data we collected from a user study with 36 participants, each of whom completed two mini-MOOCs (one in stationary and one in the on-the-go condition[4] at specific times of the day to control for daylight and crowdedness), guided by the following research questions:

RQ1: To what extent does learning on-the-go (compared to stationary learning on a mobile device) affect MOOC learners' learning gain, learning efficiency and interactions with the course content?

[3] In the remainder of this paper, we refer to learning in a non-stationary situation with a mobile device as *learning on-the-go*.

[4] In this condition our participants physically explored the university campus.

RQ2: How do learners perceive their workload (physical as well as mental) in the stationary and learning on-the-go conditions and how does it relate to their learning performance and interactions?

2 Background

Our research addresses the following aspects of online learning: multitasking and attention fragmentation, and the use of mobile devices in different learning situations, with a focus towards learning in MOOCs.

Multitasking and divided attention Interacting with a mobile device while on-the-go requires the ability to multitask and divide one's attention between several tasks efficiently at once. Multitasking—the act of attempting to engage simultaneously in two or more tasks that have independent goals [8]—is directly connected to our research on mobile learning from MOOCs.

Multitasking is tightly coupled with the attention level and situational awareness. Studies on walking and mobile use have highlighted the increase of cognitive load and a necessity to divide attention, thus forcing mobile users to correct their gait and walk slower while performing tasks on mobile devices [11, 12].

Multitasking also incurs a cost on performance and accuracy for other tasks as our ability to effectively process two or more attention-demanding tasks simultaneously is limited [8], and performance across two concurrent tasks is optimized based on perceived priorities [7]. Thus, switching between activity contexts (e.g. in the on-the-go setting switching between reading the slides, paying attention to the traffic, listening to the video lecture) lowers task effectiveness. Harvey and Pointon [10] investigated the effect of fragmented attention on mobile web search tasks in three different contexts (walking on a treadmill, navigating through an obstacle course, and sitting down) and found that the contextual situation affects user (search) task performance—walking affected participants' objective and perceived search performance negatively. In addition, participants who performed searches while on the move reported a higher difficulty and cognitive workload in performing the tasks than those sitting. In MOOC learning, which requires a high degree of attention and commitment, this indicates a potential for less effective learning in the on-the-go condition compared to the stationary one. Xiao and Wang [25] investigated the impact of divided attention on the learning process and learning outcomes for mobile MOOCs, and proposed to detect divided attention via monitoring learners' heart rate. In their study with 18 participants under lab conditions, they observed divided attention to hurt learners' performance.

With respect to multitasking and fragmented attention our study explores the effect and extent learning on-the-go has on learners' ability to comprehend course content, and on their cognitive learning performance.

Mobile learning Mobile learning (i.e. learning with a mobile device) stresses the possibility to learn across time and space, and commonly assumes that learners are on the move [22]. What mainly distinguishes mobile learning from traditional classroom learning is the variety and unpredictability of the situations in which learning can take place [20] which places different demands on learners' attention level, body posture, environment, and social context whilst learning.

Mobile technology has enabled context-sensitive learning and the use of sensor data of mobile devices to enrich the learning experience [21]. Dingler et al. [6] implemented an Android app to collect sensor data (e.g., location, ringer mode, motion) in order to detect learners' contexts and boredom levels during microlearning sessions on mobile devices. Based on a user study, the authors concluded that while on mobile and in transit people are more open to engage in quick learning sessions, and context information retrieved from phone sensors can be helpful for mobile learning.

Learning tasks that are cognitively demanding (e.g., reading and writing scientific essays) seem to be incompatible with the use of mobile phones while on-the-go, whereas activities that are less cognitively demanding (e.g., social networking, texting, taking pictures) are compatible with body movement [4]. Music et al. [14] attempted to detect changes in user attention by exploiting smartphone accelerometers to trace changes in user gait patterns as a response of interaction with a mobile device. In a traditional study setting (e.g. a library, classroom), the use of mobile phones whilst learning has been found to be a distraction for most learners [1]; the same can be said about the mobile MOOC setting as incoming notifications, messages, news, etc. can take learners' focus away from the actual learning task.

The mobile devices themselves also affect learners' perceptions. Dalipi et al. [5] studied learners' experience by comparing desktop and mobile platforms of three well-known MOOC environments (edX, Coursera, and Udacity). They found that learners were more satisfied with the respective desktop variants; mobile platforms with their small screens and a lack of external input devices caused negative emotions as a number of tasks, which were easy on the desktop variants, were rather difficult to execute on the mobile variants. In a similar vein, Becking et al. [2] argue that learning situations for learning on-the-go are uncomfortable because of the lack of space for taking notes, and the potential for interruptions.

In our study, we explore learning with a mobile device in two different settings: (i) on-the-go and (ii) in a seated and more convenient condition close to traditional online learning, yet with a mobile device. In the former condition, we do not confine our participants to the lab (e.g. by using a treadmill or an obstacle course), but instead ask them to physically explore the university campus whilst learning.

3 Study Design

3.1 Learning Situations

Inspired by the mobile search study conducted by Harvey and Pointon [10] (who found walking to impact participants workload perception and search effectiveness), we investigate whether learning on-the-go has any measurable impact on learning gain, effectiveness and perceived workload compared to stationary learning in the MOOC setting. We consider the following two learning situations (or scenarios) in our user study:

Stationary Scenario (`StaSc`): Learners study MOOCs while sitting in the office with a mobile device. This scenario is used as the baseline in order to measure the impact moving around has on learning.

Moving Scenario (`MovSc`): Learners study MOOCs with a mobile device while on-the-go. Participants are asked to learn whilst walking from one building to another on campus at their normal walking speeds, while paying attention to the traffic.

To eliminate the effects of learning behaviors unrelated to the use of mobile devices (e.g., taking notes on a piece of paper) and of different types of mobile devices, we instructed our study participants to perform all learning tasks exclusively on the same mobile device[5] in both `StaSc` and `MovSc`. We hypothesized—in line with the findings in [25]—that compared to `StaSc`, the necessary multitasking and the possible interruptions and distractions in `MovSc` negatively affect MOOC learners' learning gain. We also hypothesized that participants in `MovSc` require more time to consume the course materials (due to the divided attention) than those in `StaSc`. In line with the previous hypothesis, we anticipated participants in `MovSc` to revisit the video page more often and rewind the video more often than those in `StaSc` to refresh their memory (which was impaired due to the distractions on-the-go).

3.2 Learning Materials

We prepared four mini-MOOCs on different topics (Table 1) for our user study and deployed them on edX Edge, a low-visibility clone of the edX platform.

All four mini-MOOCs have the same structure: one lecture video and 20 knowledge questions about the video content. To ensure similar difficulty across the four mini-MOOCs, we selected them from a pool of introductory MOOC video lectures produced by the Delft University of Technology for the edX platform. We chose those four based on their similar *amount of unfamiliar terminology* as labelled by three annotators with computer science degrees. Each question is a multiple-choice question (almost all with four answer options in addition to *I don't know*), created by two of this paper's authors. These questions are not only used in the mini-MOOCs (right after the video lecture) but also in the pre-study questionnaire, which enables us to compute the knowledge gain in a straight-forward manner. This setup also means that the questions cover key knowledge concepts discussed in the respective lecture, instead of specific video details (such as the number of instructors, or the color of the background). Each question can be attempted once in the pre-study questionnaire and MOOC.

[5] A Samsung S5 smart-phone with 1080*1920 pixels, 5.1" display screen, 2GB RAM, 2.50 GHz CPU, Google Android 6.0.1 and the Chrome browser installed.

The pre-study questionnaire thus contained $4 \times 20 = 80$ questions about the four topics; we used the answers to those questions to select for each study participant the two mini-MOOCs with the *lowest* prior knowledge levels. This setup leads to large potential knowledge gains. Table 1 lists the pre-study knowledge scores for the four mini-MOOCs across our 36 participants. Note that the maximum obtainable score for the questionnaire was 20 for each topic. The Qubit topic proved to be the most difficult, with more than half of the participants answering 0 or 1 question correctly; in contrast, water quality aspects proved to be the easiest topic with half the participants answering between 7 and 11 questions correctly.

Table 1: Overview of our mini-MOOCs, the video length per MOOC and the minimum/median/maximum of participants' prior knowledge test scores on the topics. The highest possible score per topic is 20.

		Pre-study scores		
Mini-MOOC	**Video length**	**Min.**	**Median**	**Max.**
Radioactive decay	6m53s	0.0	3.0	9.0
Qubit	12m24s	0.0	1.5	16.0
Water quality aspects	10m45s	1.0	7.0	11.0
Sedimentary rocks	5m03s	0.0	4.0	10.0

3.3 Environmental Conditions

In our study, next to stationary and on-the-go, we focus on the impact of two additional environmental variables—the *light condition* and the *crowdedness of the surrounding*. It is known that daylight can affect the visibility of the screen on mobile devices [26] and the visibility of the surroundings during learning. The crowded learning situation may lead to intensive interruptions and distractions in `MovSc`. We thus hypothesized daylight and crowdedness to lead to reduced learning gains. Note that these environmental conditions only apply to `MovSc`.

Study participants were randomly assigned to one of four groups based on the time of the experiments for `MovSc`: (i) 8:45 am (crowded time with daylight), (ii) 11:00 am (uncrowded, daylight), (iii) 5:45 pm (crowded, no daylight[6]), and (iv) 8:00 pm (uncrowded, no daylight). Table 2 shows the distribution of study participants across the four groups.

3.4 User Study Steps

In our experiments, each participant was guided through the following steps.

[6] We conducted this user study in December 2017 and January 2018 in Delft, the Netherlands.

Table 2: Number of participants under different experimental conditions.

Mini-MOOC	MovSc Daylight & Crowded	MovSc Daylight & Uncrowded	MovSc Dark & Crowded	MovSc Dark & Uncrowded	StaSc
Radioactive decay	3	1	4	2	15
Qubit	3	5	3	4	13
Water quality aspects	0	2	0	0	2
Sedimentary rocks	2	0	3	4	6
Total	8	8	10	10	36

1. Pre-study questionnaire: 80 knowledge questions plus questions on demographics, experience with mobile devices, mobile learning and MOOCs;
2. In random order, complete `StaSc` and `MovSc` with the two mini-MOOCs that exhibited the lowest prior knowledge levels. During a mini-MOOC, participants were allowed to switch between the video and questions. Each of the two scenarios was assigned a 30 minute time block.
3. Post-MOOC questionnaires: after each of the two scenarios a NASA TLX workload assessment form[7] [9] had to be completed. It assesses the workload during learning in each scenario on six aspects: mental demand, physical demand, temporal demand, performance, effort, and frustration.

3.5 Metrics

We now describe how we measured participants' learning gain, learning efficiency and interactions. To measure the statistical significance of the difference between groups of learners, we employed the Mann-Whitney U test.

In our study we use *absolute learning gain (ALG)* and *realized potential learning (RPL)* to measure participants' **learning gain** [23]. *ALG* refers to the number of questions that were answered *incorrectly* in the pre-study questionnaire and *correctly* in the mini-MOOC, normalized by the total number of questions (20). *RPL* refers to the *absolute learning gain* normalized by the maximum possible learning gain[8].

We measure **learning efficiency** through the efficiency of (i) course material consumption and (ii) learning gain. For the former, the time participants spend on watching videos (i.e., *video duration* and *normalized video duration*) and answering questions (i.e., *question duration*) are calculated—as we deploy our mini-MOOCs on edX Edge, we have access to all tracking data logged by edX. As shown in Figure 1, *video duration (VD)* refers to the minutes a participant spent watching the lecture video. *Normalized video duration (NVD)* refers to

[7] `http://www.nasatlx.com/`

[8] For example, if in the pre-study questionnaire a learner answered 2 out of 20 questions correctly, the maximum possible learning gain is 18. If in the MOOC quiz two more questions are answered correctly, then ALG is $\frac{2}{20}$ and RPL is $\frac{2}{18}$.

VD normalized by the video length, which measures the proportion of the video consumed. *Question duration (QD)* refers to the minutes a participant spent on the questions, including any time spent on video rewinding. To compute the **efficiency of the learning gain**, we divide *RPL* by *VD* and *NVD*.

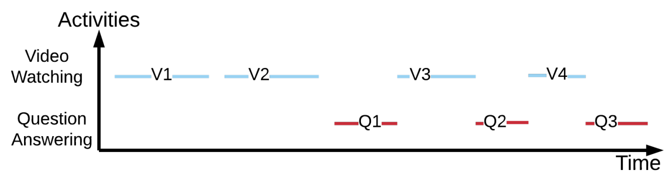

Fig. 1: An example of a participant's learning progress. In this example, *video duration (VD)* is $V_1 + V_2 + V_3 + V_4$, *initial video watching duration* is $V_1 + V_2$, *video rewinding duration (VRD)* is $V_3 + V_4$, *question duration (QD)* is $Q_1 + V_3 + Q_2 + V_4 + Q_3$, and *question answering duration* is $Q_1 + Q_2 + Q_3$.

As **interactions** metrics we consider those that lead the participant away from the default mini-MOOC path (i.e. watch the video lecture and answer the 20 quiz questions). Specifically, we use the times participants revisit the video page during question answering (i.e., *#video page revisiting, #V_revisit* in short) and the minutes participants spent on video rewinding for questions (i.e., *video rewinding duration, VRD* in short) as metrics.

3.6 Study Participants

We recruited study participants from within TU Delft's faculty of Electrical Engineering, Mathematics and Computer Science through flyers and mailing lists. 36 learners participated in our study: 9 women and 27 men. Their average age was 24.4 (std. dev. 2.7; min. 19; max. 30). Most participants were Master students, the highest educational degree (so far) was: high school (5 participants), Bachelor's degree (21) and Master's degree (10). On average, the participants had been using smart-phones for 7 years; all indicated to use them daily. 27 participants had used their mobile device for a learning activity within the last seven days before the user study. 26 participants had registered to at least one MOOC, 13 had made use of their mobile devices to learn in a MOOC and 11 participants had successfully completed at least one MOOC.

On average, each participant took about two hours to complete the entire experiment (recall, that each mini-MOOC was given a thirty minute time limit, however additional time was required for the pre-study questionnaire, switching scenarios, explanations by the experimenter, post-MOOC questionnaires and so on). Participants received a payment of €15. To motivate participants to learn, we provided a bonus payment of €5 for the participant achieving the highest learning gain overall.

4 Results

4.1 RQ1: Learning Gain, Efficiency and Interactions

In Table 3 (rows 1 & 2) we report our learning gain metrics across the two learning scenarios and the different environmental conditions, aggregated over all participants and topics. We find that, overall the learning gain achieved in the `MovSc` setting ($ALG = 0.47$) is slightly lower than in `StaSc` ($ALG = 0.5$). The difference is not significant though; similarly, the environmental conditions exhibit no consistent tendency. More concretely, as in our setup (20 questions per mini-MOOC), an ALG value of 0.05 represents one question answered correctly in the mini-MOOC but not the pre-study questionnaire, the recorded difference between `StaSc` and `MovSc` means that on average not quite one more question is answered correctly in the stationary learning scenario—this is in contrast to our hypotheses, where we expected to find considerable differences in learning gain across the two learning scenarios. The findings also hold for RPL; here a value of 0.05 means that 5% of those questions not answered correctly in the pre-study questionnaire are answered correctly in the mini-MOOC.

Table 3: The average value and standard deviation of metrics about participants' learning gain, learning efficiency and interactions under different experimental variables. † indicates significance at $p < 0.1$ level. ‡ indicates significance at $p < 0.05$ level. ⋄ indicates significance at $p < 0.01$ level.

	Learning Situation		MovSc with different environmental variables			
Metrics	StaSc (S)	MovSc (M)	Daylight & Crowded (DlC)	Daylight & Uncrowded (DlU)	Dark & Crowded (DkC)	Dark & Uncrowded (DkU)
ALG	0.504(±0.130)	0.474(±0.145)	0.463(±0.155)	0.463(±0.074)	0.480(±0.164)	0.485(±0.178)
RPL	0.575(±0.140)	0.533(±0.164)	$^{DkU\dagger S\dagger}$0.484(±0.161)	0.550(±0.125)	0.536(±0.177)	0.554(±0.195)
VD (minutes)	10.796(±3.929)	11.883(±4.125)	10.881(±4.577)	^{S‡}13.179(±1.937)	11.068(±5.131)	12.463(±4.139)
NVD	1.304(±0.572)	1.407(±0.519)	^{DkU†}1.312(±0.468)	^{DkU†}1.187(±0.189)	1.457(±0.716)	^{S‡}1.609(±0.486)
QD (minutes)	16.284(±6.754)	^{S‡}12.581(±6.323)	^{S†}12.142(±6.983)	13.913(±6.551)	^{S†}12.703(±6.833)	^{S‡}11.745(±5.916)
RPL/VD	0.074(±0.080)	^{S†}0.053(±0.029)	0.053(±0.029)	^{S‡}0.043(±0.013)	0.063(±0.040)	0.050(±0.026)
RPL/NVD	0.583(±0.531)	^{S†}0.419(±0.170)	$^{S\ddagger DlU\dagger}$0.384(±0.126)	0.475(±0.138)	0.459(±0.236)	$^{S\ddagger DlU\dagger}$0.363(±0.141)
VRD (minutes)	4.515(±4.514)	$^{S\diamond}$2.284(±3.416)	^{S‡}2.102(±3.523)	^{S‡}2.048(±3.485)	^{S†}2.698(±4.406)	^{S†}2.203(±2.568)
#V_Revisit	5.056(±5.270)	$^{S\diamond}$2.250(±2.708)	^{S†}2.500(±3.546)	$^{S\diamond}$1.125(±1.356)	^{S†}2.700(±3.093)	^{S†}2.500(±2.506)

In terms of **learning efficiency**, the results in Table 3 (rows 3 to 7) show that in line with our hypotheses, participants in the `MovSc` scenario did take slightly more time to consume the lecture videos than those in the `StaSc` scenario. Importantly, participants spent significantly more time on questions in `StaSc` (on average 16 minutes) than in `MovSc` (13 minutes), a finding that corresponds to the results in [10] where stationary and on-the-go mobile web search tasks were compared. This result can be explained by the fact that a comfortable and stationary environment allows participants to engage with in-depth tasks requiring

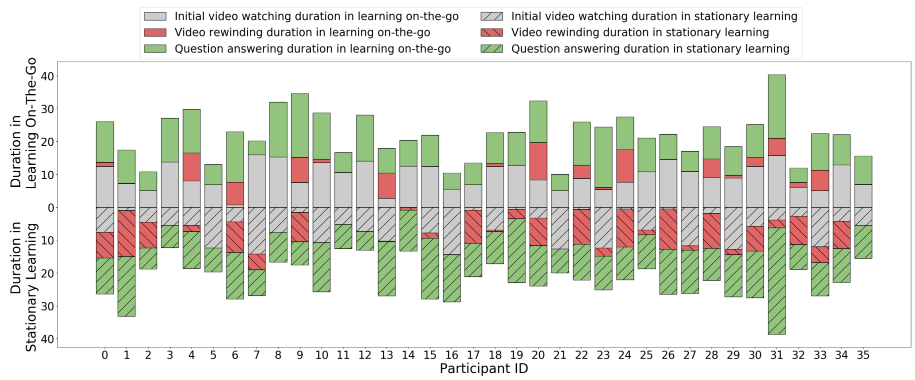

Fig. 2: The time participants spend on difference activities in `StaSc` and `MovSc`.

a lot of focus. Remember though, that this additional time spent on questions did not result in significantly higher learning gains as seen in our previous analyses. Once again, when considering the impact of the environmental variables, we do not observe a consistent trend, one way or another.

To determine the **efficiency of learning gain**, we measure how much participants learn from video watching. We hypothesized that `MovSc` has a negative impact on participants' efficiency of learning gain. *RPL/VD* refers to participants' learning gain *per minute of video watching*. We find that on average participants in `StaSc` reach a 40% higher efficiency (statistically significant) than in `MovSc`. We again did not observe clear trends for the different environmental variables.

When we consider **learners' interactions** in Table 3 (rows 8 & 9) it is evident that on average participants in `StaSc` spend nearly twice as much time rewinding the videos than those in `MovSc`. The same trend holds for the number of times participants revisit the video playing page during question answering. Both of these findings indicate that in `StaSc` participants put more effort on finding relevant information for question answering than in `MovSc`. In order to understand participants' interactions in more detail, in Figure 2 we plot on a per-participant basis their (i) video watching duration before they start question answering (i.e., *initial video watching duration*), (ii) their *video rewinding duration* during question answering and (iii) their time spent on question answering only (i.e., *question answering duration*).

Compared to `StaSc`, it is evident that participants in the `MovSc` scenario tend to spend more time on video watching before they start question answering and less time on question answering. During question answering, most participants in `MovSc` revisited the video playing page fewer times and spent less time on video rewinding than in `StaSc`. This finding shows that participants in `MovSc` tend to switch less between the video playing page and the question page than those in `StaSc`. An explanation for the long question answering duration in `StaSc` can be that question answering is an activity with higher cognitive demand than video watching, which is not as compatible as video watching with walking with a mobile device [3].

4.2 RQ2: Learning and Perceived Workload

We now investigate the relationships between participants' learning and their workload perception. Concretely, we report the Pearson correlation coefficient between our learning & interaction metrics and the six aspects of workload participants self-reported via the NASA TLX form. The results are shown in Figure 3; here, *TLX score* is the overall score of workload, and *MentDmd, PhysDmd, TempDmd, Perform, Effort, Frustr* are participants' workload scores on mental demand, physical demand, temporal demand, performance, effort, and frustration respectively.

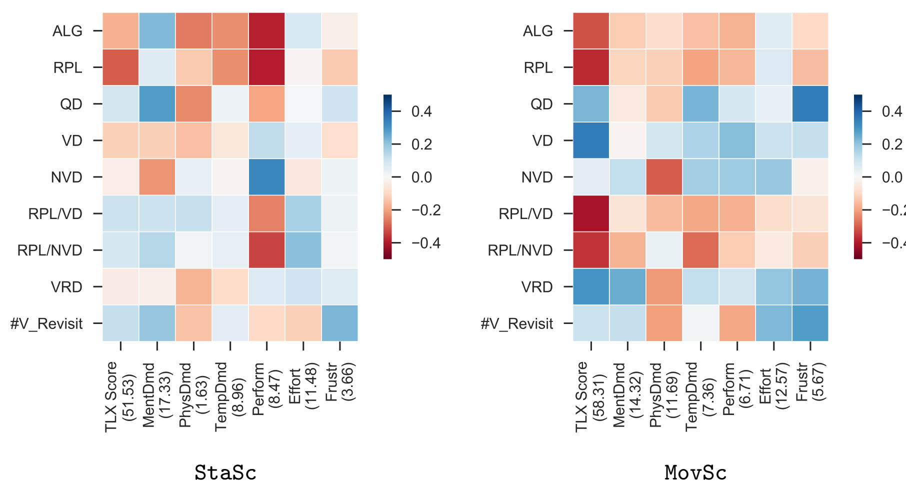

Fig. 3: Linear correlation coefficient between participants' learning performance, interactions and their perceived workload as measured through the NASA TLX form. The x-axis label also shows the average score of each workload dimension across our participants.

When comparing `StaSc` and `MovSc` we observe sensible results with respect to mental demand and physical demands: in both scenarios the mental demand was found to be the most important one, followed by the physical demand in `MovSc` (in contrast to `StaSc`, where the physical demand received the lowest average weighting).

In `StaSc` we find performance (*How successful were you in accomplishing what you were asked to do?* with answer options ranging from *Poor* to *Good*) to be negatively correlated with learning gain, i.e. our participants were not able to estimate their own learning success very well. In contrast, performance is positively correlated with *normalized video duration*, indicating that participants estimated their learning performance to at least some extent based on how much of the video content they watched.

In the `MovSc` scenario, participants were also not able to self-estimate their learning gains (we found a slight negative correlation between ALG/RPL and performance); most interesting though is the positive correlation between *frustration* and question duration, i.e. the longer participants in the on-the-go condition spent answering questions, the more frustrated they felt (though overall frustration was not a major workload dimension).

5 Conclusions and Future Work

In this paper, we investigated to what extent learning on-the-go (compared to stationary learning on a mobile device) and its requirement for divided attention and multitasking affects MOOC learners' learning gain, learning efficiency and interactions with course content. Our investigation included a foray into the influence environmental variables (light conditions and crowdedness) have on mobile learning. A second research question we considered is the relationship between learners' perceived workload and their learning.

In order to explore these questions, we designed a user study with 36 participants; each participant "followed" two mini-MOOCs deployed on the edX Edge platform: one in the on-the-go condition (learning on a mobile device while walking) and one in the stationary condition (learning on a mobile device while being stationary). We measured participants' learning through a set of pre/post-study multiple choice question sets. Our analyses resulted in the following key findings:

- On average, learning on-the-go (`MovSc`) results in a lower (-6% in ALG) learning gain than stationary learning (`StaSc`) with a mobile device.
- Compared to `MovSc`, `StaSc` participants spent 29% more time on answering questions and reached a 40% higher learning efficiency.
- When it comes to workload perception, participants in both conditions were not able to estimate their performance (wrt. learning gain) well; `MovSc` participants reported higher physical demands and slightly higher frustration than participants in the `StaSc` condition, though the differences in learning gains were small (first key finding).
- The environmental variables we investigated (daylight and crowdedness) did not have a consistent impact on any of the metrics investigated.

Our study has several limitations, among them the size of the user study (36 participants in total) which provides us with trends but few significant differences. A second limitation is the simplification of the on-the-go scenario to a walk on the campus (which does improve though—in terms of realism—on the lab conditions in prior studies). As pointed out by Becking et al. [2], the learning situation might be more complicated and unstable in many situations. Learners may walk, wait or take a bus or train while learning with a mobile device. Additionally, we only considered two environmental variables—the light condition and the crowdedness; other variables such as the weather and the temperature (recall that we conducted the experiments during December/January, i.e. the winter season in Europe) were not considered, although they are likely to also affect our participants' behaviour. For example, two participants who were assigned the 8pm timeslots for the study told us that they aimed to finish their learning sessions as quickly as possible due to the bad weather. In the future to measure learners' interactions in more complex learning situations, a dedicated mobile app may be needed to record fine-grained details of learners' contexts and actions whilst on-the-go.

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