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PAPER

Estimating Learning Task Duration: Modelling Within an Intentional Activity Framework

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ABSTRACT

This paper investigates the problem of estimating optimal task duration. The study specifically focused on e-learning, higher education, language learning and self-study contexts. The problem of duration was approached through secondary analysis that made use of an intentional activity framework. This was supported by a small classroom learning analytic study of mobile multiple-choice intentional duration. The research's value was exemplified through the further creation of an original model that estimates maximum task duration by deconstructing task complexity within open and distributed learning (ODL) contexts. The model uses six basic building blocks to enable the timing of any given intentional learning task. It will provide organisational clarity to conference presenters, EdTech developers, lecturers, materials designers, and teachers. It can help to predict the phase in the lecture or lesson cycle when well-intentioned learners go off task. It is likely the framework can be applied to broad categories of activity, such as, ODL, sports, traditional education, and the workplace. The study supports both the six-minute e-learning video rule and the ten-minute rule for lectures, providing insight as to why these rules generally seem to be effective. This is the optimisation of engagement and can be applied to any scenario in which engagement is a key metric. In addition, the framework may be beneficial to the field of human activity detection.

KEYWORDS

time on task, actual learning time, engagement, intentionality of action, intention in action, task complexity

1 INTRODUCTION

For at least 45 years [1]–[5], the rule of thumb for optimal learning task-duration has been about 10 minutes, maybe 15 or 20. However, the lack of data behind previous attempts to offer a standard duration for learning tasks has come under critical examination [6] [7]. More recently, open and distributed learning (ODL) video engagement data has suggested that six minutes is a useful duration for watching e-learning video [8]. In a separate study, four minutes was identified as a good

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duration for app-based mobile-assisted language learning (MALL) multiple-choice quizzes [9]. The consensus from the literature [10], is that extracting meaningful data on the interplay of study intention, human attention and overall engagement is very difficult. This difficulty arises because measuring these aspects is challenging, attempts to measure have not used uniform units of measurement, and much of the data is based on samples that lack statistical significance [11]. Consequently, many ODL, teaching and lecturing practitioners have accepted (or not) ten-minutes as an approximate standard. This choice is intuitive, provides useful time structure, and until now, there has been no meaningful alternative.

The time on task hypothesis has been the focus of attempts to understand the relationship between time and successful task completion since the 1960s [12] [13]. It was previously suggested that increased time on task leads to increased learning in classroom and workplace settings [14] [15]. However, more recently, attention has been placed on the inconsistency in results, demonstrating that the relationship between time and learning outcomes remains poorly understood [12]. Carrol's model attempted to explain learning as a function of five variables: time allocated to learning, perseverance (time engaged in learning), time needed to learn, quality of instruction and ability to learn [10] [13]. There has been a tendency to focus on the first variable: time allocated to learning (for example, [16]–[18]). However, very little is known about how time is used [19]–[21].

However, this paper asserts that Carrol's second variable, learner engagement (perseverance), and therefore productivity of learning time, can be optimised by focusing on the relationship between complexity and duration of intentional learning tasks. Over the years, many researchers, EdTech developers, and teachers have noticed that the actual time on task should be limited for optimal results [1] [2] [5] [9]. But it is challenging to identify precisely how to do this, as the optimal duration of tasks is hidden within larger units of activity. Student attention is cyclical, as it tends to wax and wane throughout an extended lesson period [6] [7]. For instance, students in a classroom context do not typically shut down and go to sleep. Instead, their intention to learn, along with wider social conventions, jostles with their limited capacity to maintain attention. Essentially, the student's state of readiness fluctuates as they drift in and out of Vygotsky's zone of proximal development [22].

A popular rule of thumb for task time is known as the ten-minute rule. It was initially conceptualised for lectures but has been broadly applied to teaching. However, it is based on little actual empirical data. Indeed, research into student attention spans is very limited [23]. According to Bradbury [6], the ten-minute rule mostly stems from the influence of a paper by Hartley and Davies [3]. It appears intuitively and experientially to have appealed to practitioners' perceptions of common sense for at least 45 years.

This study has modelled available statistically significant data and provides an explanation for the variation in task duration based on task complexity that ODL developers, teachers and lecturers can apply to task design within the current school learning and ODL paradigms. The model is based on a secondary analysis of several sources of very large learning analytic datasets, collected from multiple-choice, e-learning video and interactive video mobile and web-based activities. The model's unit of measurement relies on a new conceptual framework that allows for the deconstruction of tasks. The study supports both the six-minute video and ten-minute lecture rules, providing insight as to why and how both these rules generally seem to be effective. The emphasis during the study was on ODL and language learning. However, the results can be applied very broadly and are likely to be of interest to both ODL and traditional classroom practitioners.

2 A FRAMEWORK FOR THE PROBLEM OF TASK DURATION

The study is concerned with optimising educational tasks in terms of time spent. A new adapted framework has been formulated, utilising three concepts taken from activity theory and three concepts from intention in action. The combination of these concepts allows for a better understanding of the complexity and duration of any task. If a practitioner understands one concept—adjacent operation—then they will greatly increase their control over material design and instructional practice.

2.1 Activity-theoretical framework

This study is multidisciplinary; it concerns applied linguistics, computer science, education, philosophy, psychology and, more broadly, social science. To bring these disciplines together, an adapted activity-theoretical framework was placed over the study. Based on activity theory as articulated by Leont'ev [24], the study breaks activity into three units of investigation: activity, action, and operation. It is assumed that while the intention to undertake purposeful activity is a conscious decision [25], the time allotted to the mechanisms (operations and actions) in the activity appears somewhat subconscious on the part of the learner. The teacher may intend a task to last 15 minutes, but this does not mean the well-intentioned student will learn for 15 minutes. Intention has a limit. The study uses a version of the activity theory framework based on average strength of learning intention and explains what a task is in activity-theoretical terms. Once the complexity of a given ODL learning task is defined, it is possible to calculate a model of task duration.

2.2 Intentionality of action

According to Mele and Moser, a person intentionally performs an action at time t, only if, at time t, they have an action plan that includes or guides the action. And they follow the action plan [26]. In simple layman's terms, intentional action is not luck; you mean to do it and you do it. According to Bonicalzi and Haggard, the concept of intentional action helps us understand our own sense of self and our interaction with the environment [27]. Higher and further education, ODL, self-study and self-study EdTech are all based on the premise of an intention to learn. The Pacherie conceptual framework for the phenomenology of action places an emphasis on intention in action making a distinction between three levels of intention: motor, proximal and distal [28]. Distal intention is concerned with future intentions [29] [30]. In a classroom, a menu on the whiteboard of today's tasks would serve as a distal intentional roadmap to the next hour's series of proximal intentional tasks. Proximal intention is concerned with the act of doing now, executing the guidance provided by distal intention. Motor intention is concerned with the physical procedures of the proximal tasks. For example, picking up the tablet device and looking at the words on the screen.

2.3 Three defined units of activity

Activity is the largest unit within scope. This includes 90-minute lessons or essay writing activities but can also include entire courses of study. Generally, teachers and learners understand and are conscious of activity. They prepare materials that they expect to use, such as books, computers, paper, and pens. In ODL, the instructor has probably given the learner guidance on how long the lesson or course will take.

Actions are the mid-sized units. Actions are typical learning tasks, such as a reading comprehension task, taking a multiple-choice quiz, or watching a video. The lesson activity is comprised of several actions. Teachers and students generally understand when they are undertaking an action or task. Action is the practical unit of teaching and learning. For learners, including ODL, they occur in the present moment of learning. However, to understand an action unit, there is a need to dissect it into basic operations. Operations are not obvious; they are hidden in plain sight. Once revealed, a better understanding of teaching and learning is brought into consciousness.

Operations are the smallest unit of activity and are used to build actions. This study defines six basic operations of learning: input based on eyes and ears, intentional thought (in, out) and output based on hands and mouth. It is possible for some activities, such as sports, to express output using other body parts and input using other senses (smell or touch). But generally, ears, eyes, hands, and mouth with thought-in and thought-out work for most academic and ODL contexts. The six basic operations are further expressed within learning tasks in the form of clicking, listening, making, reading, speaking, watching, and writing. The six basic operations represent cognitive, sensory, and motor skills that are helpful to practitioners. For clarification, the reason for including the variable thought-out is that speaking and writing require two steps: mental formulation of a response and then physical delivery of that response.

A teacher, developer, or learner can, with awareness, recognise these six generic operations seated within the learning tasks they use or create. Consequently, they can calculate a modelled optimal duration for the tasks based on the number of generic operations in play. It is a working assumption that most learning tasks can be reduced to six operations. See Table 1.

Table 1. Expression of six basic operations

Basic	Expression
Ears	Listening
Eyes	Reading, watching
Hands	Clicking, making, and writing
Mouth	Speaking
Thought-in	Input
Thought-out	Output

2.4 Modified conceptual framework for intention in action

Pacherie's articulated conceptual framework and dynamic model of intention [28] is not broad enough to frame language education or ODL. Listening does not include a motor skill but is a skill central to many learning situations. In language learning activities, listening is as important as reading, speaking, and writing. It holds equal weight. Searle [31] briefly addresses listening as an action of non-movement. If I order a student to listen, and they listen, then the student has undertaken an intentional action. It does not require motor skill. More generally, in a lecture hall, classroom, or ODL context, students tend to spend a lot of time listening and then cognitively processing the information. This is intentional action. They may, or may not, go on to use movement: make, read, speak, use, or write. Therefore, it seems appropriate to replace motor intention with the concept of adjacent intention. Adjacent intention is more expansive than Pacherie's motor intention; it accounts for intentional action involving motor and non-motor skills that are required for learning activities. It can account for listening as an operation and quiet thought as an undetectable but real operation. Proximal intention is unchanged; it maps directly onto action, and importantly, it will place Leont'ev's action very concretely in the present moment. Distal intention is a useful concept that can be mapped as the overarching intention of the activity (lesson) and can also be left concerned with the full potential of future broader activities such as courses and life-learning goals. Therein, this is a modified conceptual framework for intention in action: adjacent intention, proximal intention, and distal intention.

It is important to understand that all three levels begin in the present moment: adjacent intention can be measured in seconds from now; proximal intention is likely measured in minutes from now; and distal intention may be measured in minutes, hours, days, months, or years from now. Together, in combination, by using adjacent and proximal intentional building blocks with the over-the-horizon vision of distal intention, humans have built the world we inhabit. The three levels of intentional action are the basis of learning, development, and progress.

In a learning context, distal intention triggered at the beginning of a lesson or course is future-orientated, looking beyond the now. It provides a reason to stay in the classroom or on the device, even when we are tired, bored, or just feel the impulse to be somewhere else. Adjacent and proximal intentions are the reasons we learn right now, in this moment. Operations and actions are time-bound; in ODL and m-learning, they can start anytime [32], but they still must end. In contrast, distal intention can continue throughout a lifetime; it is the reason an individual achieves success and ODL is effective. Distal intention provides the intention to complete multiple actions, to plan ahead, and then execute that plan, one proximal action at a time.

2.5 A new intentional activity framework

The modified conceptual framework for intention in action can be combined with the previously defined units of activity. In doing so, a proposed time-bound intentional adaptation of the activity theory framework is produced. Activity theory includes a sense of individual intention, but this new adapted framework is more directed. If we know the amount of time taken to perform a proximal action and we can deconstruct the proximal action into adjacent operations, then we can predict, or at least model, both time and complexity for any action of that type.

This adapted framework provides three key concepts by combining intentional action with activity theory. Since intention is already a component of activity theory, it is possible to omit the word intention from the terms. We are not adding intention but rather specific types of intention and binding these intentions to start in the present moment of learning within specific forms of learning activity: adjacent operation, proximal action, and distal activity.

Figure 1 illustrates how these concepts will relate to educational environments and beyond.

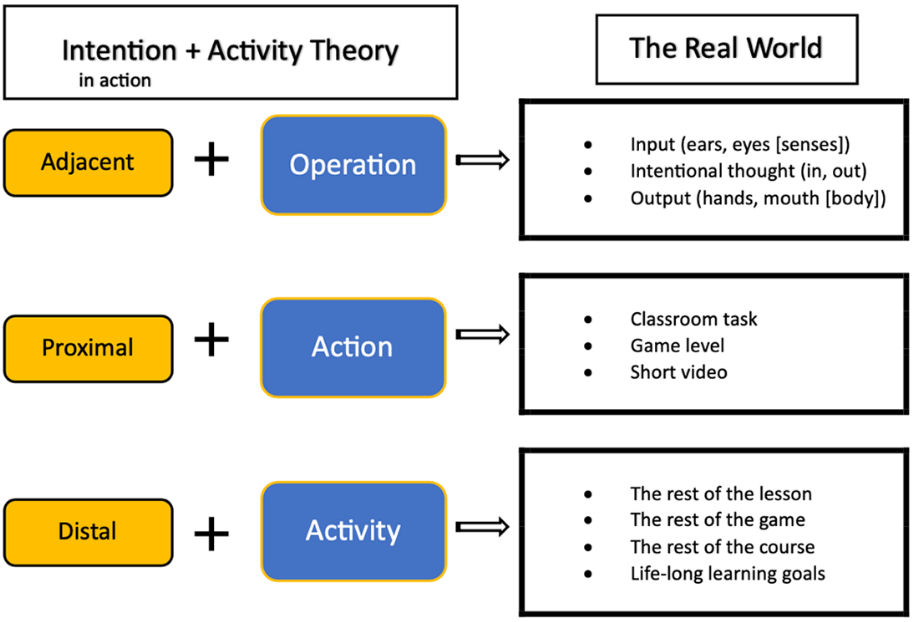

Fig. 1. Intentional activity framework

It is important for developers, learners, lecturers, and teachers to become more aware of the six basic adjacent operations. This will not only reveal the advisable duration of tasks but also aspects of the difficulty of performing a task. Practitioners and users can become more cognisant of the level of challenge being undertaken.

3 PROBLEMS AND HYPOTHESIS

Now that a framework has been developed it can be applied to problems of task complexity and duration.

3.1 The problems of complex task duration

Task duration directly affects ODL and classroom engagement. A model that calculates the maximum advisable duration of a task based on the complexity of the task was the primary motivation for creating the new adapted framework.

Attention span limits proximal action. The proximal intention to act can trigger an actual act at any given moment. However, once triggered, the clock starts ticking. Proximal action is then limited by the human ability to remain focused and concentrated in the present moment. This is more commonly known as attention span. This may be moderated by complexity—the number of adjacent operations within the action. Furthermore, the time limitation of proximal action exists in every action; it can be personally experienced and is repeatable. Try reading a difficult book. Time yourself. When do you begin to lose attention, skip words and drift? About four minutes?

Optimising duration of proximal action. If a learning action does not account for the limited duration of proximal intention, then the productivity of the learning action will decrease with time as the student's state of readiness also declines. It must eventually inhibit learning. At some point, the learner will literally, while in a learning context, switch off and the directed proximal action will stop. For example, the learner starts to daydream (please see Figure 2). Then, at somewhat random points in time, for often arbitrary reasons, proximal intention will reset, the student will become ready, and learning action will continue. This abrupt, juddery, cyclical wave of learning is the norm of learning experience [23]. When this norm is juxtaposed against what the teacher is attempting to teach, it cannot be optimal. Teaching and ODL practice must be aligned with the learner's state of readiness and human cognitive limitations. A step towards optimisation can occur by building learning tasks based on units of proximal action. The goal must be to prevent proximal intention from falling off the proverbial cliff. There may still be judder (see Figure 2), but a more stable, more present learning interaction should lead to greater learning output.

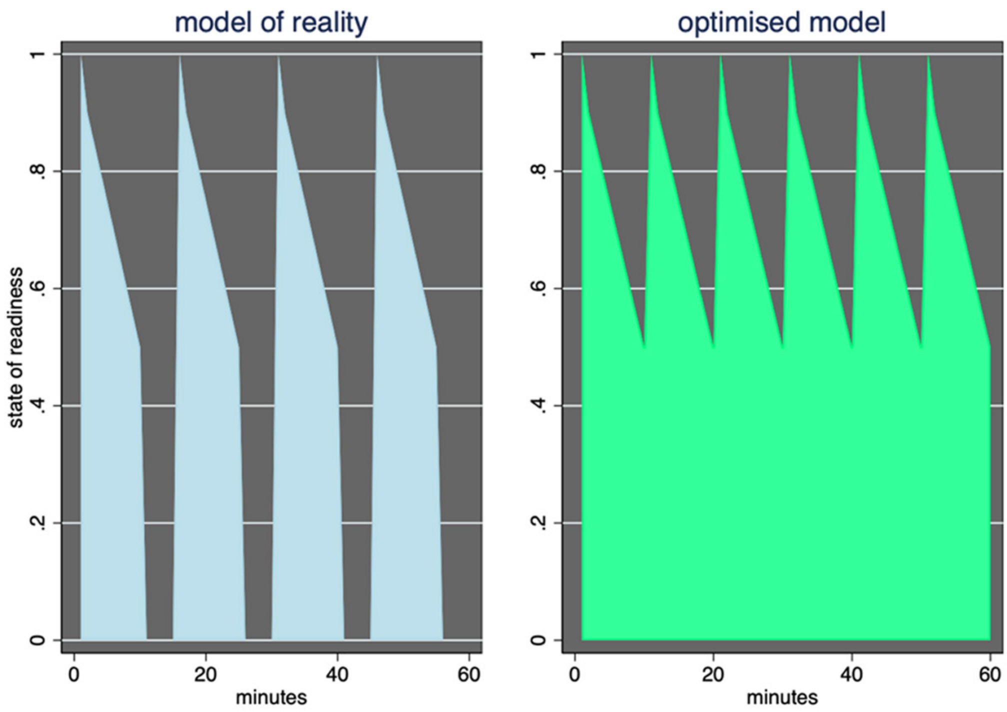

Fig. 2. Student state of readiness during 60-minute lesson activity

Controlling for complexity to model time on task. The new framework for intentional activity is useful for approaching the issue of time on task. As previously stated, learning tasks are examples of proximal actions. Maximum proximal action duration (time on task) is defined as the amount of time that a user will spend on a set of adjacent operations before they essentially switch off. This will vary with the complexity of the task and is based on the average user's intention to spend time on a task. It will likely fall within an optimal range. Since a learning task is defined as a proximal action, there is logically a need to control distal activity and adjacent operations.

Controlling distal activity. Distal activity duration is the duration of an activity comprised of a series of proximal actions. Examples of distal activity are 60-minute lessons and full game play. It is likely that in many contexts, distal activity duration is defined by policymakers or EdTech developers, and it is likely to vary with learner type and context. A maximum value for life-long learning is the time of death. A minimum value is one proximal action. Therefore, distal activity is equal to one or more proximal actions. It is possible within a model of a learning task to reduce distal activity to one proximal action. It will play no further role in the analysis.

Controlling adjacent operation. How long does it take to think? How long do the physical eye movements induced by reading last? Are they of equal duration? This is for the fields of cognitive science, neuroscience, and psychology to consider. While it may inform human-computer interaction research, it is beyond the scope of this study and has limited practical pedagogical value. To control for adjacent operations, there is a need for adjacent operations to be countable and to simplify adjacent operation duration to a modelled value for each of those counted adjacent operations. This builds a practical model of task duration: The study asserts that it has greater utility than the currently employed rules of thumb.

3.2 Hypothesis

A modelled value for adjacent operation duration will be helpful in demonstrating that actual proximal action (task) durations, as found in the literature, are correlated to the complexity of the underlying adjacent operations. Proximal actions are built from combinations of adjacent operations; consequently, proximal action duration is modelled from the sum of those adjacent operations' durations. It can be hypothesised that if it is possible to map actual real-world task duration to summed model adjacent operation duration, then the model can be used to predict an approximate advisable maximum duration for any future real-world task.

H1: Optimal task duration is correlated to underlying task complexity.
H2: The optimal task duration can be estimated by summing adjacent operations.

4 METHODS

The aim of the study was to use the new, adapted framework of activity to unravel the complexity of action and model the duration of tasks. As outlined in this section, a secondary analysis was undertaken of previous research by applying the adapted framework to the data, and a small confirmatory classroom study was used in support. Modelling conditions and assumptions are also defined.

4.1 Secondary analysis

There is surprisingly little actual data on attention span duration and learning [23]. Only five studies were found that provided data on the duration of a learning task. Three are related to ODL videos, one to a multiple-choice language learning app, and one to university lectures. The ten-minute rule was probably a consequence of this difficulty in collecting data. The data that does exist is relatively modern, device-driven analytics engagement data. Engagement can act as a proxy for intention to a certain extent; it indicates when a person chooses to stop, but it does not precisely explain when the intention to act has ended.

Only three of the studies found met the criteria of this project. They could be deconstructed into operations, were statistically significant, and could be compared. Fortuitously, they provide the parameters of a simple model of adjacent operation duration. The multiple-choice MALL app study [9] provides a two-adjacent operation task; the 6.7 million video view study [8] provides a three-adjacent operation task; and a second video with interaction study [33] provides both three and four adjacent operation tasks. This data affords the possibility to model task duration.

4.2 Classroom study

The multiple-choice study, while providing interesting results on optimal intentional quiz level length, had only an estimated duration [9]. In order to further support the secondary analysis, a small classroom-based experiment was undertaken at a university in Japan. The same multiple-choice quiz app was used in a classroom setting. The quiz levels were set to 12 question sets. Four tablets were placed at the front of the room. To decrease the teacher effect, students were told in a low-key manner that to make conversational working groups smaller, one student would rotate to the multiple-choice quiz. They would take turns. The students were told they did not have to do it and should stop as soon as they felt bored or lost interest. They decided when the rotation occurred or if it occurred. The room lent itself to the relaxed ambiance of a free, independent choice. It was a large room, and a space of several meters was placed between the two activities. The students had to move to use the tablets but were not compelled to do so. It required personal intention. In fact, only an initial request for the first volunteers was made. No one else was asked. They opted to rotate. This sense of relaxed self-intention was important to at least partially mimic self-study ODL intention.

The only data collected was accumulative time in seconds, recorded after every quiz question was answered. The cohort of 28 participants were Japanese, 18–25 years old, including 12 female and 16 male university students. Informed consent was received from the students. It was explained that data was being recorded on the tablets for research purposes. It was further explained that the students did not have to use the tablets. However, ultimately, it was a normal educational activity presented as a teaching strategy to help make conversation groups smaller while offering something of potential interest to individual students.

4.3 Modelling assumptions for duration of a single adjacent operation

The six basic adjacent operation types are generally assigned equal weight within the model. The caveat is that a weight of zero is assigned to rapid, almost instinctive operations, such as clicking. Clicks are almost reflexive, basically quick statements such as A or B. Multiple-choice quizzes are also comprised of a series of very quick actions: eyes, thought-in, thought-out, click. It was assumed that in addition to the removal of clicking, the very rapid, thought-out operation could also be given a weight of zero. Allocating a value such as 0.1 would be arbitrary; the data does not lend itself to such precision. This is true of all other values, as a weight of 1.0 is also an arbitrary value. The 1.0-weighted operations involve intention and involve more than reflex, so they were given equal weight. In addition, further analysis led to the tentative assumption that an adjacent operation can only be counted once per action. For example, a discussion may involve three speakers, meaning a learner will listen three times, but this is reduced to one learning operation of listening per action. It has also been assumed that thought-in can handle multiple inputs at high speed. Therefore, listening, reading, and watching, if they occur simultaneously or overlap within the same sequence of user experience (action), require only one thought-in adjacent operation, as framed in this model.

By finding mean average duration values for tasks during secondary analysis, it is possible to break the tasks (proximal actions) down into adjacent operations and estimate a modelled variable for singular adjacent operation duration. Thus, it is possible to provide model durational values for all proximal actions with known countable adjacent operations. ODL and classroom practitioner task duration decisions, as the results will demonstrate, can now be refined, supported, and largely explained.

5 RESULTS

This is an important area of inquiry. It could affect everyone who learns. An analysis was undertaken of the three remaining studies, Byrne [9], Geri et al. [33] and Guo et al. [8], that provided mean average data for tasks (proximal actions). Each proximal action was broken down into adjacent operations. This provided each study with an average value for adjacent operation duration. In addition, the classroom study supported these results. 28 students were offered the chance to play within a conversational English class on two occasions, one week apart, and this led to 53 plays. It was noted that two students did not elect to play on either occasion. 30 of the plays were for 12 or more questions. The previous study had modelled multiple-choice duration at 240 seconds for 12 questions [9]. The classroom study found the average intentional duration was 264.2 seconds for a minimum of 12 questions answered. However, the previous multiple-choice study had also concluded that question set lengths of greater than seven and less than 15 were equally viable, suggesting a durational range of 140–300 seconds with a median value of 220 seconds [9]. In the classroom study, the average duration for completions greater than seven questions was 233 seconds for 39 plays. The classroom data, although limited, strongly supports the MALL study findings and estimations.

The mean average value of the four studies was taken as the model's singular value for an adjacent operation of learning: This is 124.9 seconds. As can be seen in Table 2, 124.9 seconds sit within a narrow range of 110–143.4 seconds. Therefore, the model duration of actions with 2–4 adjacent operations is reflective of the actual e-learning task data.

Table 2. Calculating duration for an adjacent operation of learning

Study	Action	Operations (Ops)	No. of Ops	Time Secs	Seconds Per Op
Classroom	Multiple choice 8+ questions answered	Eyes 1.0, Thought-in 1.0, (Thought-out 0.0 + Click 0.0).	2	233	116.5
[9]	Multiple choice median 11 question quiz	Eyes 1.0, Thought-in 1.0, (Thought-out 0.0 + Click 0.0).	2	220	110
[33]	E-learning video	Eyes 1.0, Ears 1.0, Thought-in 1.0.	3	430.2	143.4
[33]	E-learning video with interactive questions	Eyes 1.0, Ears 1.0, Thought-in 1.0, Thought out 1.0 (+ Click 0.0).	4	538.8	134.7
[8]	MOOCs videos	Eyes 1.0, Ears 1.0, Thought-in 1.0.	3	360	120
Average duration per adjacent operation of learning					**124.9**

5.1 Number of operations in learning tasks

The data provides values for operations of lengths one to four. However, what is the likely range of operations within typical actions? Table 3 provides task operation examples based on EFL tasks. Since the tasks are skills-based, they are likely to hold true for other subject areas.

Table 3. Model duration for EFL learning tasks

Skill	Task/Action	Operations (Ops)	Number of Ops
Think	Think about the topic	Thought-in	1
Read	Reading only	Eyes + thought-in	2
	Reading vocabulary check	Eyes + thought-in + thought-out (+ click/check)	3
	Reading comprehension check	Eyes + thought-in + thought-out (+ click/check)	3
Listen	Listen only	Ears + thought-in	2
	Listen comprehension check	Ears + thought-in + thought-out (+ click/check)	3
	Video only	Eyes + ears + thought-in	3
	Interactive video	Eyes + ears + thought-in + thought-out (+ click)	4
Write	Writing outline	Thought-in + thought-out + hands	3
	Paragraph main idea sentence(s)	Thought-in + thought-out + hands	3
	Paragraph supporting example sentence(s)	Thought-in + thought-out + hands	3
Speak	Discussion cycle	A: Thought-out + eyes + mouth	5
		B: Eyes + ears + thought-in + thought-out + mouth	
		A: Ears + thought-in + (eyes)	

The discussion cycle (Table 3) is a good example of how it is possible to reduce operations. If we sum the total of the 10 (11) adjacent operations of the basic discussion cycle pattern, then the modelled limit could be over 20 minutes. However, within one discussion, the listen and speak operations are in synchronised A-B complementary pairs; meaning the discussion set should be reduced to only five adjacent operations for small groups. Essentially, we only count each basic operation once within an action.

5.2 A simple linear model of duration

The analysis of the data in Table 2 is revealing. An average adjacent operation takes about 124.9 seconds (about 2.08 minutes). It is possible to have a singular adjacent operation based proximal action: think or be quiet. However, educational proximal actions tend to be formed by two to four adjacent operations (see Tables 2 and 3). This suggests proximal action for learning typically falls roughly between 4.14 minutes and 8.28 minutes (see Figure 3).

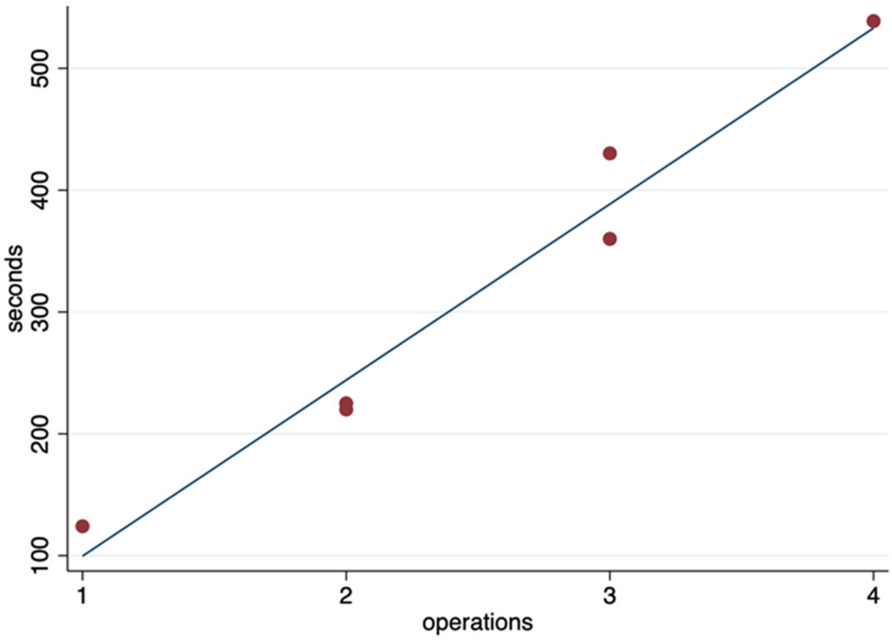

Fig. 3. Linear fit of the data

The available data for adjacent operations one to four shows a rate of change of 2.3 minutes per operation. The data appears to be relatively linear. This supports both hypotheses H1 and H2. It suggests a correlation between the complexity of the task and its duration. Each operation could be simply summed with an additional 2.08 or 2.3 minutes. Since six generic operation types in ODL (ears, eyes, thought-in, thought-out, hands and mouth) appear to place a practical limit on action, the maximum durational value can be modelled as approximately 13 minutes as illustrated in Table 4.

Table 4. Proximal action duration in minutes

Operations	Duration Based on Linear Sum 2.08	Operations	Duration Based on Rate of Change 2.3
1	2.08	1	2.08
2	4.16	2	4.38
3	6.24	3	6.68
4	8.32	4	8.98
5	10.40	5	11.28
6	12.48	6	13.58

6 DISCUSSION

Intention is a minimum requirement for optimal learning. But this study asserts that this becomes time-limited while active in the present moment (proximal). Proximal action must be broken down into a small enough bite to be completed within the time limits of attention. This is the study's assertion of a basic time-bound building block of learning. From the moment students' start, it is a question of when they will stop, not the presumed time when they will finish. Stop and finish may not efficiently align unless time has been controlled. Tasks must be limited to human attentional capability to produce optimal output.

Since the data was most likely based on maximum values of engagement rather than optimal values, it makes sense to simplify the model by rounding down 2.3 or 2.08 minutes to a countable base unit of 2 minutes per adjacent operation. This is extendable to a likely maximum of 12 minutes per proximal action. The model provides an estimate of time that improves how practitioners approach teaching and learning and can be calibrated to any given learning action.

The model is best presented in graph form as shown in Figure 4. The line represents the model's maximum values of duration per number of operations undertaken. If a practitioner's task duration is above the line, then it is likely that learning is being inhibited by task time. Students will be switching off. It is hypothesised that optimal learning will occur just below the line. The task duration will be between 2 and 12 minutes. The model is based on data supporting H1 and itself provides support for H2.

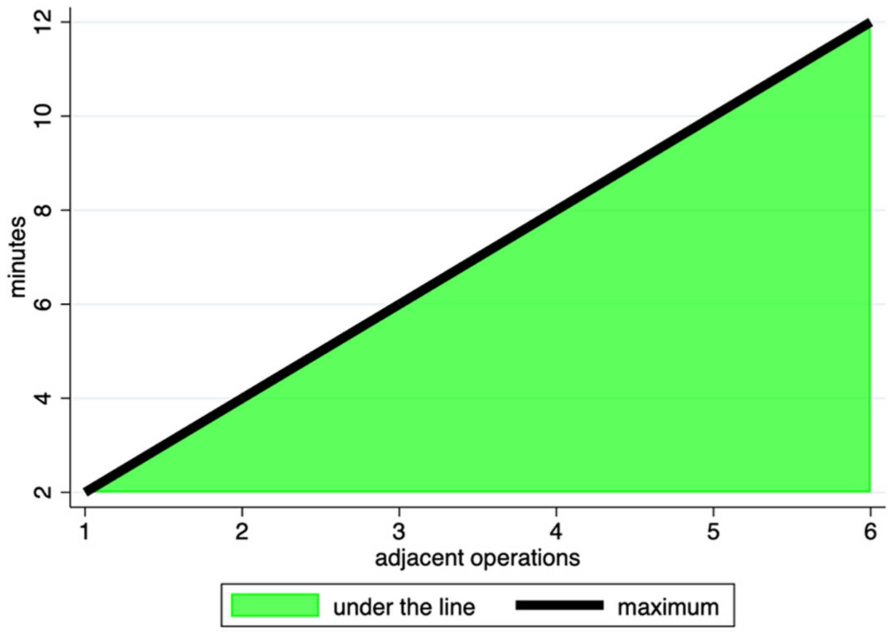

Fig. 4. Maximum duration per number of adjacent operations

6.1 Optimising ODL language learning

Language learning, whether through ODL or classroom-based methods, often utilises tasks of short duration due to the limited communicative ability of students in the target language. An analysis of typical language learning tasks suggests many learning tasks should be limited to about 6 minutes. Interestingly, the operations shown for writing actions in Table 3, if summed for a four-paragraph essay activity, would indicate a writing time of about 54 minutes (12 minutes per paragraph and 6 minutes to outline), plus we might allow an additional 6 minutes for proofreading and topic sentences. This is typically what is expected of students in classrooms and on tests. The implication is that these timings, particularly in ODL self-study contexts, can help to improve test-writing skills by deconstructing writing activity into very precise units of time-bound intentional action.

6.2 Lecture and presentation timing

Students who have good intentions to listen and think (ears and thought-in), will keep focus for about four minutes. If they take notes (thought-out and hands), then they will manage eight minutes before they drift from the lecture. If the lecturer has nice slides to read or view and/or is watchable (eyes), then about ten minutes. It seems the ten-minute rule is about right for lectures if the audience is required to perform five operations, but it could be as low as four minutes. This will make a huge difference in the quality of the learning experience over a 50-minute lecture. It is beyond the scope of this paper, but Bligh [1] offers some good suggestions on how to construct a lecture from smaller chunks.

6.3 ODL video presentation timing

In an ODL context, the lecture analysis provides a concrete time framework for the basic video presentation style. If the video task follows the basic ears, eyes, and thought-in pattern, then the six-minute rule is appropriate. However, if a practitioner wishes to extend the video task to follow the ten-minute rule, then it will require interactivity and probably the need to compel users to use thought-out and their hands extensively (write or do) while watching. Clicking tasks only afford eight minutes.

6.4 Limitations

What unintentional (non-learning) operations were users performing? We don't know if they were talking, eating, or sending an email. In fact, many of the studies were less than forthcoming on even the intentional operations users had performed. For example, watching videos could be a precise statement of fact or not precise at all. These limitations are related to the lack of available studies. The limited data provided a linear result. However, it is hoped that this study will provide a framework that may lead to more research and more comparable data. It is likely that complex actions could provide a curvilinear result. For example, marginal utility could decrease with every summed operation. This may mean the five operations for lectures should not be a linear 10 minutes but significantly less. ODL access to learning analytic engagement data could inform further study in this area.

6.5 Future research

The research has shown a correlation between task complexity and duration (H1) and provided a framework to deconstruct task activity. However, while it supports the estimation of new task duration (H2) through the model, this does require further research. In addition, a framework of time-bound intentional activity opens many areas of exploration that could lead to improved practice. Distal activity, while defined, was not within the scope of the investigation. This could prove fertile investigative ground. Furthermore, it was hypothesised that optimal learning duration would be just below the maximum line, as seen in Figure 4. This is challenging to precisely identify but will be an interesting area of research that can be supported by learning analytics. Recently, studies in human activity detection have allowed estimation of attention span based on head posture [34]. If human activity detection research were placed within the intentional activity framework, then more accurate results on task duration may be forthcoming. A fourth area of interest would be a more nuanced evaluation of adjacent operations. It is very likely that just as clicking was deemed to be of less value to attention longevity, perhaps reading should have a different weight to listening and writing a different weight to speaking.

7 CONCLUSION

The framework and model can be applied to any activity where there is a need to organise the task in the present moment in terms of human capability with long-term goals in view: for example, creative collaboration, education, ODL, team sports, and the workplace. An intentional activity framework and model of task duration can provide answers to ODL practitioners about the maximum length a specific task should have. While only a model, it is arguably precise enough for the classroom and general ODL massive open online course (MOOC) contexts but could be further refined for ODL learner-centred approaches. The analysis, based on adjacent operations, generally supports the 6-minute video rule and the 10-minute lecture rule. Furthermore, the framework and model can provide practitioners with insight into task complexity. It is also likely that the framework and model will provide structure for new technologies, such as human detection instrumentation, to measure task complexity and duration more precisely.

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