# Understanding Personal Data Tracking and Sensemaking Practices for Self-Directed Learning in Non-classroom and Non-computer-based Contexts

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## ABSTRACT

Self-directed learning is becoming a significant skill for learners. However, learners may suffer from difficulties such as distractions, a lack of motivation, and so on. While self-tracking technologies have the potential to address these challenges, existing tools and systems mainly focused on tracking computer-based learning data in classroom contexts. Little is known about how students track and make sense of their learning data from non-classroom learning activities and which types of learning data are personally meaningful for learners. In this paper, we conducted a qualitative study with 24 users of Timing, a mobile learning tracking application in China. Our findings indicated that users tracked a variety of qualitative learning data (e.g., videos, photos of learning materials, and emotions) and made sense of this data using different strategies such as observing behavioral and contextual details in videos. We then provided implications for designing non-classroom and non-computer-based personal learning tracking tools.

## CCS CONCEPTS

• **Human-centered computing → Human computer interaction (HCI)**; *Empirical studies in HCI*.

## KEYWORDS

personal informatics, self-tracking, non-classroom-based learning, non-computer-based learning, self-directed learning, behavior change

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## 1 INTRODUCTION

In recent years, learning independently and autonomously has become a trend among high school and college students [9]. Emphasizing individual learning, self-directed learning (SDL) is one of the most significant theories that enables learners to proactively engage in a variety of different learning strategies. These include diagnosing learning needs, formulating learning goals, identifying resources for learning, choosing and implementing appropriate learning strategies, as well as evaluating learning outcomes independently or collaboratively [42]. SDL is commonplace not only in the classroom but also in a variety of places such as the home and library. Since the onset of COVID-19, students have to take classes, complete assignments, and prepare for exams at home, which requires them to be highly self-directed. SDL is beneficial for individuals in terms of equipping learners with leadership ability [51], promoting adaptive problem-solving skills to achieve learning goals [32], and shaping a positive attitude towards learning [62]. However, when studying alone, being a productive self-directed learner is difficult. Individuals may suffer from being easily distracted [55] or having poor motivation [13, 44, 60]. In addition, students may struggle with establishing the metacognition that supports them while analyzing their learning performance.

Tracking and making sense of personal data can facilitate behavior change [45], and keep people accountable to goals [11]. It has the potential to address the aforementioned challenges of being a self-directed learner (i.e., distraction, lack of motivation, and difficulty in establishing metacognition for analyzing learning performance). However, it is challenging to design such trackers for learning activities that occur in a non-computer-based context. For instance, most class material, exercise books, and tests in middle schools in China and Hong Kong are paper-based. The majority of learning tracking systems predominantly adopt automated tracking methods to collect and visualize course-based data on a computer [53, 67], which fail to capture the behaviors that occur external to digital devices. For instance, these systems cannot track analog learning activities when a learner completes an assignment in an exercise book. Another challenge is that students may find it difficult to interpret visualization feedback from analytical learning systems due to their lack of data analytic literacy [46]. Moreover, the trackers' visualization feedback cannot provide adequate contextual information beyond numeric data [40]. Finally, most learning tracking systems emphasize group data, which does not include valuable individual data [34].

To address the challenges with the data collection approaches that are adopted and the types of data that are collected by current learning tracking tools, we studied Timing, a popular learning tracking mobile app in China. In Timing, users manually track their learning data in various forms, such as via videos, photos, and text paragraphs. Most of the users who employ Timing are senior high school students and college students. These users are preparing for competitive college entrance exams or the national entrance examination for postgraduates. Success on these exams requires students to take their own initiative to study diligently, especially when participating in self-directed learning. The above context makes Timing the ideal application to study how current tracking practices support self-directed learning in non-classroom and non-computer-based learning contexts. The current study explores the following research questions:

- **RQ1**: Why are students motivated to use Timing to track learning data in non-classroom and non-computer-based contexts?
- **RQ2**: What kinds of non-classroom and non-computer-based learning data do students track using Timing and how?
- **RQ3**: How do students make sense of non-classroom and non-computer-based learning data with Timing?

To answer these questions, we conducted a qualitative, interview-based study with 24 participants who actively documented and shared their learning data on Timing. We found that users chose to use Timing for different reasons, such as being attracted to the engaging tracking features. The most common motivation was to collect personal learning data to monitor and evaluate one's learning performance while studying alone. We found that interviewees predominantly tracked a wide spectrum of qualitative learning data, including learning process videos, learning outcomes (e.g., photos of finished assignments, test sheets, or notes), learning tasks, and their emotions. When it came to making sense of tracked data, interviewees noted they meticulously observed several elements in videos, including their changing gestures and facial expressions, surrounding environment, and learning content (e.g., assignments or test papers). In addition, they quickly glanced through static visual data such as learning schedules, photos, or emotional states to motivate themselves and remind themselves to keep learning. Moreover, interviewees migrated across different types of data to gather information about contextual details and validate their preliminary assumptions about learning performance. Finally, when reflecting on the different data that they tracked, interviewees manually recorded their insights about how to improve their performance in the future in sentence-form.

This research makes the following contributions:

- An empirical description of why learners track their learning data, what types of learning data they track, and how they track such data using Timing in non-classroom and non-computer-based contexts.
- A nuanced understanding of how learners make sense of the data they tracked using Timing.
- A discussion of how non-classroom and non-computer-based tracking and reflection behaviors effectively support self-directed learning, and design implications for future learning tracking tools that support non-classroom and non-computer-based learning activities.

## 2 RELATED WORK

This research is inspired by, and builds upon, prior research on Self-directed Learning, Data Tracking Paradigms in Personal Informatics, and the Sensemaking of Tracking Data.

### 2.1 Self-directed Learning (SDL) and Its Challenges

Defined by Knowels, self-directed learning (SDL) is a process that enables learners to proactively engage in diagnosing their learning needs, formulating learning goals, identifying resources for learning, choosing and implementing appropriate learning strategies, as well as evaluating the learning outcomes independently or collaboratively [41]. The study of SDL has extended this concept to include different models from the perspective of personal attributes and a learning process [7, 8, 29]. Costa and Kallick described SDL as occurring in three phases: self-managing, self-monitoring and self-modifying [18]. In recent years, the role of context has been emphasized as a focal point to better understand SDL, which has not been fully examined before [7]. For example, commonplace online learning environments (e.g., MOOCs and knowledge-sharing live streams (KSLSs) [47, 48]) have provided learners with the flexibility to have agency over their learning pace, which shifts the context of SDL from offline to online. Based on the online context, Song et al. extended the prior models to understand how online learning environments influenced SDL in terms of resource use, strategy use, motivation, planning, monitoring, and evaluating [61].

However, when studying alone, such as at home or in a library, it is difficult to become a productive self-directed learner. Without intervention from formal classrooms (e.g., teachers), students typically suffer from three challenges: (1) Students' attention is easily drawn by the app on phones or tablets. Several studies have found that students may struggle with maintaining focus when executing a task [55, 65], (2) Students may lack ample motivation when studying alone [55]. Previous research has revealed that the lack of self-motivation was one of the major obstacles to self-directed learning pursuits [60]. (3) Students may feel it challenging to establish metacognition that supports them in analyzing their performance in terms of learning task completion. Prior research has indicated that many students lack the metacognitive skills to be aware of the mistakes in their learning strategies [13]. Even for high-ability students, developing metacognitive learning strategies may not be easy [6].

## 2.2 Technologies that Support Self-directed Learning

Various technologies have shown the potential of addressing some of the challenges that exist with self-directed learning. For example, attention issues. Prior literature has noted that smartphones lead to distraction and negatively impact productivity and self-regulation, among others [38]. To address challenges with concentration, Ko et al. [43] developed a mobile application that leveraged synchronous group consciousness to limit smartphone usage behaviors for the sake of enabling users to concentrate on group activities. Meanwhile, Kim et al. [38] designed a smartphone-based intervention tool that required users to devote additional time and perform lock-out tasks before gaining access to apps. While this line of research has demonstrated effectiveness in discouraging smartphone usage behavior, the aforementioned prototypes did not support the evaluation of learning performance, which is one of the most significant aspects of self-directed learning.

On the other hand, another line of research about tracking technologies showed their potential to support self-directed learning [31, 35–37, 63, 70]. For example, Govaerts developed a tool to visualize the data tracked in different learning environments, which enabled students to better understand their learning behaviors [31]. Work by Karaoglan Yilmaz et al. claimed that personalized feedback from experts (e.g., experienced teachers) about students' learning analytics reports could benefit students by identifying learning deficiencies, supporting students' self-assessment, and improving students' academic performance [36].

In other research, in the context of learning tracking, learning analytics systems automatically capture system-based learning data from students in the same class, including the frequency of social interactions, time expenditures, course content usage, and academic performance [53, 67]. This learning data is then analyzed to generate different types of visualizations, called Learning Analytics dashboards(LADs). For example, Lim et al. developed a course-based system to capture and display students' study hours, course activities, and course completion [46].

However, tracking learning activities using entirely automated methods has several limitations. First, automated tracking cannot capture the activities that are performed without digital devices (e.g., completing a paper-based exercise book). Second, automatic tracking fails to capture multi-device activities. For example, even if a learning tracking system shows that a user has spent 40 hours on a web-based assignment, the user may have watched videos on a different device [40].

It is apparent that current automatic tracking techniques cannot capture non-classroom and non-computer-based learning activities, which occur within textbooks, exercise books, text papers, and so on. Little is known about how a learning tracker should be designed to enable students to track and reflect on their learning activities in these contexts. This gap in the literature motivated the present investigation into students' learning tracking behaviors on Timing.

## 2.3 Sensemaking with Tracked Data

Sensemaking refers to *"how a person understands and reacts to a situation in a given context"* [21], or how individuals understand their situation, cope with gaps, and direct the behaviors with the usage of their, and other people's, observations. Sensemaking in HCI is guided by Russell's model [59], i.e., people create representations (e.g. diagrams, maps or tables) to organize information to answer complex questions.

In personal informatics research, people use several strategies to make sense of their personal data based on the type of data they have collected. When it comes to briefly and frequently monitoring real-time behavior, for instance checking step counts on an activity tracker while walking from the canteen to one's dormitory, users often make sense of the data by quickly glancing at a screen [30]. Prior research has demonstrated that glancing could increase long-term commitments to physical exercise as a way of reminding users to be accountable to their goals [14]. To obtain deep and reflective insights from data, users often employ analytical approaches. Choe and colleagues reported several sensemaking approaches that were used by quantify-selfers, i.e., noticing details, self-reflecting on data, identifying trends, making comparisons, and identifying correlations [10]. Some users also track several types of data at the same time, which requires a different approach compared to sensemaking about a single type of data. For example, to identify their ovulation period, women were found to track various data such as cycle day, basal body temperature, and symptoms [19]. Women interpreted such data by integrating different indicators and the emotional factors associated with fertility tracking [19]. When women made sense of menstrual cycle data, they tended to observe what they tracked and paid attention to the accuracy of the data to change their thinking and practices around it, rather than changing the results (i.e., timing of occurrence) [24].

Moreover, how people make sense of tracked data may be more complicated than the assumptions held by tracker designers. For example, when evaluating productivity, knowledge workers assessed their mental state, attitude towards work, and the benefits of a task, rather than assessing the amount of time spent on tasks [39]. Alternatively, when making sense of data, people sometimes annotated their data because they felt that automatically generated data was insufficient to reflect their feelings or values [17]. For example, to better express their feelings beyond a specific tracked activity, users leveraged SnapPI (a data-driven sticker authoring tool) to modify their data in an exaggerated way and post it on Snapchat [68].

Within the context of learning tracking, visualization techniques such as bar charts, pie charts, and timelines are widely used in the learning analytics dashboards of course-based systems [53]. Similar to [10], the users of such systems used analytical approaches to make sense of their data. The most frequently adopted method is to make comparisons with peers' data, since LADs emphasize group-based learning data. For example, prior research demonstrated that participants' attention was constantly drawn to a cohort's learning data about the time spent on course tasks and completion progress [46]. However, given that the visualizations in the LADs were the only feedback available, users may not have been able to make sense of the LADs' data due to their lack of data analytics literacy [46]. Recent studies have demonstrated that it is challenging for some students to interpret visualizations, which leads to confusion [58] or misinterpretation [46]. Other research has found that the frame of reference of visualization could negatively impact a learner's emotions. For example, showing how


**Figure 1: Examples of Timing usage: (a) Users shared every aspect of learning in learning diaries, (b) Users recorded their learning process in the form of learning videos by using the front-facing camera on their mobile devices, (c) Timer, which calculated the time users spent on a specific task. Users could label the name of a task, and (d) Learning video recording interfaces.**

students fell behind in the class through LADs could result in negative emotions [46]. Since this line of research mainly focused on the sensemaking of learning data within a computer-based context, it remains unclear how students make sense of data about non-classroom and non-computer-based learning activities, as well as the types of challenges they encounter during the process of sensemaking. The present research was thus motivated to fill these research gaps.

## 3 TIMING: A LEARNING DATA TRACKING APPLICATION

Timing is a learning tracking application that aims to help users improve their learning efficiency and cope with procrastination. Most of the users on Timing are students. A prior report [3] indicated that the number of users has been significantly increasing since the outbreak of Covid-19 in December 2019.

One of the most prominent functions in Timing is its learning diaries (Figure 1a), which enable the recording of every aspect of learning, in the form of photos or screenshots. These include learning schedules, assignments, test papers, and thoughts. Another important feature is learning video recording (Figure 1b), which enables users to capture their learning process using the front-facing camera of their mobile phones. To record a learning video, a user needs to tap on the video recording button in Timing, which activates the front camera and enables the smartphone to display the camera's view on screen. Next, the user begins the learning video recording by tapping on the "start learning" button. While recording, the user can tap on the "end" recording button to quit shooting footage (Figure 1d). Once completed, Timing automatically edits this video, generating a sped-up version lasting between 20-30 seconds and automatically uploads it to the user's public feed. Users can share their learning diaries and videos publicly in Timing and "like" and comment on the posts from other people. Some users may use the timer function (Figure 1c) to calculate the time they spend on a specific task. And users could label the name of a task in the timer.

## 4 METHOD

From January to February 2021, we remotely conducted 24 semi-structured interviews with Timing users to understand how their tracking practices supported SDL behaviors.

**Table 1: Summary of users interviewed. Among the 24 participants, 20 are female and 4 are male, aged from 13 to 27. All are students whose educational backgrounds range from junior high school to Master's.**

| ID | Age | Gender | Education Level | App Usage (months) | Number of Users Following | Number of Followers |
|---|---|---|---|---|---|---|
| **P1** | 13-17 | Female | Junior High School | 25 | 27 | 15 |
| **P2** | 18-22 | Female | Undergraduate | 54 | 40 | 1389 |
| **P3** | 23-27 | Male | Graduate | 13 | 52 | 80 |
| **P4** | 23-27 | Female | Graduate | 18 | 5 | 20 |
| **P5** | 23-27 | Female | Graduate | 12 | 112 | 601 |
| **P6** | 18-22 | Male | Undergraduate | 14 | 31 | 104 |
| **P7** | 18-22 | Female | Undergraduate | 21 | 48 | 88 |
| **P8** | 23-27 | Female | Graduate | 38 | 370 | 3108 |
| **P9** | 13-17 | Female | Senior High School | 5 | 0 | 2170 |
| **P10** | 23-27 | Female | Graduate | 27 | 95 | 151 |
| **P11** | 18-22 | Female | Undergraduate | 9 | 79 | 36 |
| **P12** | 18-22 | Female | Undergraduate | 24 | 62 | 102 |
| **P13** | 18-22 | Male | Undergraduate | 13 | 4 | 5 |
| **P14** | 13-17 | Female | Undergraduate | 19 | 36 | 4665 |
| **P15** | 13-17 | Female | Senior High School | 10 | 55 | 57 |
| **P16** | 18-22 | Female | Undergraduate | 24 | 126 | 26 |
| **P17** | 18-22 | Female | Undergraduate | 6 | 71 | 25 |
| **P18** | 18-22 | Female | Undergraduate | 13 | 11 | 1 |
| **P19** | 18-22 | Female | Senior High School | 14 | 69 | 40 |
| **P20** | 13-17 | Female | Junior High School | 11 | 102 | 234 |
| **P21** | 18-22 | Female | Undergraduate | 28 | 40 | 4653 |
| **P22** | 18-22 | Female | Senior High School | 26 | 67 | 83 |
| **P23** | 18-22 | Male | Senior High School | 11 | 70 | 76 |
| **P24** | 18-22 | Female | Senior High School | 23 | 86 | 677 |

## 4.1 Participants

Our participants were recruited through direct contact and snowball sampling. We invited 12 Timing users to participate in the interviews, and these users then referred other Timing users that they kept in contact with. Through snowball sampling, we recruited 12 participants. Among the 24 participants (Table 1), 20 identified as female, and 4 identified as male. Their age ranged from 13 to 27 years. All participants were students, with educational backgrounds ranging from junior high school to Master's. All of their native languages were Chinese. Twenty-three of the participants studied in China, and one of them studied in the UK. At the time the interviews were conducted, 17 participants had used Timing for at least one year, and the other 5 participants had used it for at least 5 months. Our sample covered a variety of users in terms of duration of usage, number of following, and followers. It was worth noting that the usage of Timing was not specific to the lockdown period. Most of the participants began using Timing before the outbreak of COVID-19. At the time when we conducted interviews, the lockdown period had ended and participants had continued to use the app to track their learning outside the classroom while they studied by themselves at home or in the library, in the evening or on the weekend.

Most of our participants were preparing for highly competitive National College Entrance Exams (NCEE) or the national entrance examination for postgraduates. For example, people use the saying "one-test-to-determine-a-life" to describe the significance of NCEE. Taking NCEE is the only way that Chinese students can get into universities. The competition of getting a high score in NCEE to pass the borderline of elite universities is extremely intense [69]. In 2021, only 1.67% NCEE candidates (183,000 out of 10.947 million) got into prestigious universities [52]. Since the NCEE occurs only once a year, the cost of failure is high. Meanwhile, social recognition and high-quality educational resources incline to elite universities further intensify competitiveness [57]. Lastly, preparing for such exams is grueling. Students must devote a significant amount of time to independently practice on test papers and engage in intensive reflection on their studies, especially in the year leading up to the exam. [64].

## 4.2 Interview Protocol

The semi-structured interviews lasted between 35 and 150 minutes. Participants were asked why they chose to use Timing as their tracking application, what kinds of data they used Timing to record, how they made sense of the collected data, and whether, how the social aspects of Timing influenced their usage behavior, and what challenges they encountered while they used Timing to track their learning data. The interviews were conducted through WeChat and QQ voice calls, which were audio-recorded and later transcribed in Chinese by two authors (native Mandarin speakers). The Institutional Review Board at our institution approved our interviews before we started to collect data. During interview, we encouraged participants to reference their own Timing pages and logs while talking about the learning experience supported by Timing.

## 4.3 Data Analysis

An open coding method was employed to analyze the interview transcripts [15]. Two of the authors coded the data individually and compared and discussed the data to gain a consensus about the results. The research team then transcribed the data in English and utilized affinity diagramming [33] to analyze the data as a modified version of the grounded theory approach [15]. The research team transcribed the codes on sticky notes with random arrangements. After several iterations, the sticky notes were arranged into a hierarchy of themes and a consensus on the general patterns of users' tracking practices on Timing was reached. For the sake of protecting participants' identities, personally identifiable information was blurred in the screenshots and anonymized using pseudonyms.

# 5 FINDINGS

This section presents the results of our study. First, we report on users' mixed goals for using Timing, e.g., to monitor and evaluate self-directed learning in non-classroom contexts, and to acquire a passion for learning. Then, we present the types and characteristics of personal learning data that users tracked in non-classroom and non-computer-based contexts and how they tracked this data. Finally, we describe how users make sense of their personal learning data.

## 5.1 Motivations for Tracking Personal Learning Data (RQ1)

Drawing on the responses from the semi-structured interviews, we found that individuals chose to use Timing for a variety of reasons. Participants were attracted to the tracking features that Timing afforded. They also valued the learning environment fostered by Timing, where every student was committed to focusing on their studies. The most common goal was to be productive and self-disciplined when studying alone.

*5.1.1 Being Motivated to Persevere.* Our data indicated three factors motivating the participants to persevere: learning evidence, presence of others, and social functionalities. Many participants chose Timing to acquire a passion for learning. Due to its lack of feedback, participants noted that it was inevitable to be demotivated when learning alone. The tracked data was perceived to be evidence of one's learning, offering immediate and intuitive feedback regarding learning progress, which motivated participants to continue studying.

> *"I could see how much effort I have devoted to the particular subjects and how many tasks I have completed. It felt like telling me I was making progress."* (P3)

Since the outbreak of COVID-19, the surge in newcomers and the frequent updating of tracked posts fostered an ambiance where every student strove to improve learning performance, motivating P14 to adjust her learning states and remain committed to her studies.

> *"There were a lot of students tracking their learning data in Timing during the COVID-19 pandemic. I felt gratified to view other users' learning data, which inspired me to track my data and work towards my learning goals — getting a good score on the National College Entrance Exam."* (P14)

Different from the above two factors, participants showed mixed feelings towards Timing's social features. Some of them noted that social functions (i.e., comments, and 'likes') could provide them with a sense of encouragement: *"It is nice to see others click 'like' or leave comments such as 'well done' for my post (data). I feel like all my hardworking has gained appreciation"(P7).* While some participants valued the social features, other participants regarded Timing as a stand-alone app: *"I am here to track and evaluate my productivity and attention, not for social ... sometimes other people's posts distract my attention, which wastes my precious learning time"(P6).* A few participants even noted that they had not used Timing for a while, because they were *"feeling overwhelmed by seeing other users' data on posts" (P17).*

*5.1.2 Enhancing Self-Discipline.* Participants noted that they were actively looking for learning apps that could facilitate self-motivated learning while alone, especially those who were preparing for college or graduate school entrance exams during the COVID-19 lockdown period. Due to the outbreak of COVID-19, all participants had to learn at home. The lack of learning ambiance made it challenging to maintain a productive learning state. Our participants considered Timing as a timely tool for monitoring and evaluating their learning performance during COVID-19, e.g.,

> *"During the lockdown period, Timing was helpful in monitoring my learning states. It supported me in following plans, helped me develop the habit of getting up early, and spurred me to persist in my learning efforts."* (P12)

*5.1.3 Recording learning in various formats was engaging.* Participants noted that Timing provided multiple functions to assist with their learning recordings, such as via videos, photos, and texts. Tracking these was appealing as these data formats could showcase their holistic learning experience, e.g.,

> *"I think it is necessary to record learning experiences from different aspects, from the learning process to outcomes. Using diverse modalities to log my learning data could provide me with sufficient material to reflect on."* (P2)

Compared with other learning tracking applications that only allowed for logging the length of their learning span, P6 noted that Timing's greatest advantage was its multimodal tracking features, as the tracked data supported by these features produced visually rich and engaging feedback, e.g., *"The dynamic and colorful visual effect from the videos and photos about my learning made me feel delighted and fulfilled. I would say I enjoy reviewing these records"(P6).*

## 5.2 Which Personal Learning Data was Tracked in Timing and How (RQ2)?

Drawing on the analysis of the personal data that was tracked by participants using Timing, we categorized the tracked learning data according to the learning timeline: the learning schedule prior to undertaking learning tasks, the learning process, and the learning outcome. In addition to learning data, we found that participants also tracked their emotions during learning activities.

*5.2.1 Learning Schedule.* Before starting to learn, participants noted that they usually developed learning schedules (Figure 2) in order to outline the tasks they intended to perform. They formulated learning plans with detailed tasks allocated to predetermined time-frames. The plan sheets were documented in the form of photos or screenshots. Keeping a record of their learning plans was seen as a reliable way for preserve and review purposes, as their physical record might be accidentally lost, e.g., *"in case I lost my original draft, I would post the photo version on Timing"* (P3). We then described features of learning schedule from three aspects: (1) time span, (2) physical or digital medium, and (3) visual design.

*(1) Time Span.* Drawing on the plan sheets shared by participants, we identified several types of sheets that differed in their time span: daily planning (n=107), weekly planning (n=30), monthly planning (n=19), and yearly planning (n=9). We found that middle school users preferred to use daily and weekly plan sheets, while college users frequently utilized monthly or yearly planning sheets.

*(2) Physical or Digital Medium.* Diverging from prior research [5, 11], in which users only used paper for tracking, Timing users documented their learning plan either physically or digitally. Middle school users often used paper trackers, as mobile devices were not allowed in school. Some participants designed their trackers using notebooks or blank paper, while others recorded their learning tasks in the whitespace and margins of printed timetables to save time, e.g., *"there are no obvious changes about the weekly learning tasks ... developing a study plan on the printed syllable reduces the burden of drawing a new one"* (P2). On the other hand, college users preferred to document their schedules on digital devices, such as typing on memos, writing on tablets, or logging in DIY spreadsheets, as they found it more flexible and portable to define tasks in this manner, e.g., *" I can easily edit my plan if my schedule changes ... since there is no limitation of writing pages, I can record as much content as I want"* (P14).

*(3) Visual Design.* Participants shared a minimalistic and pragmatic philosophy about the visual design of trackers. When asked why they did not pursue the use of artistic visual designs such as those found in bullet journals on Instagram [5], participants noted that their priority was to create trackers that were efficient and easy to use due to their stressful and competitive learning environments, especially for high school participants, e.g., *"for me, adding too decorative elements is a waste of time. I must make full use of every second to prepare for exams"* (P6). Additionally, participants believed that the artistic style used in journals and planners would cause distraction and information overload during their reflection processes, e.g., *"too many visual elements can be distracting. Sometimes my eyes are really fatigued after reviewing the schedule decorative with complex visual elements"* (P2).

*5.2.2 Learning Process.* We found that users tracked their learning process using different forms of media, including video recordings (Figure 3) that emphasized capturing experience and a timer that recorded the duration of a learning activity (Figure 4).

***Videos.*** Participants used video recording features to capture their short-term learning process, which was often less than 5 hours, and had it converted into a sped-up video once the recording ended. The videos (Figure 3b) included various learning activities, such as reading, working on exercise books, writing notes, and watching online course videos. The camera also usually captured the surrounding environment, such as one's desk, the people passing by, and the wall behind the participant.

Most participants noted that they anticipated the sped-up videos to be visually pleasing. For example, before starting to record, P2 would prepare by fixing her shooting angle and ensuring that her desk was tidy, e.g., *"before shooting, I often set up an angle that mainly includes learning materials and my upper body... I also value visual effects and personal images ... thus I make sure to clean off my desk"*. Once the recording was complete, P13 would watch the entire video again to check for any flaws that could be fixed during post-editing, e.g., *"I would undoubtedly replay the video, to ensure its quality and review any parts that require further editing"*.

Capturing learning process videos was perceived to be an effective way that enabled users to stay focused on tasks. Participants noted that positioning their mobile phones in front of their faces created a sense of monitoring, e.g., *"it feels like being monitored by the camera, which pushes me to perform better"* (P2). Tracking their learning process videos required participants to continually open the recording interface, because the app required that it be open while recording. Quitting the recording interface would stop the recording, which was undesirable for participants. This feature prevented participants from using their mobile phones for other purposes, e.g., *"when recording, I could not chat with my friends on my mobile phone ... it helped me to focus on my tasks"* (P14). The real-time recording feature also served as a mirror, allowing participants to quickly notice when they were losing focus, e.g., *"whenever I got distracted, my gaze would move away from my exercise books... I would raise my head slightly and look at the screen, which would let me know that I was not focused"* (P22). Despite the benefits of capturing the learning process, it sometimes might pose challenges in certain learning environments. Several participants who were college students mentioned that when they self-studied in dorm rooms and used Timimg to track their learning activities, their roommates' items were sometimes inadvertently captured by the camera, as multiple college students usually shared one room in university dormitories in China. They expressed that they struggled to capture essential information (e.g., textbooks and their own faces) while protecting the privacy of others in their learning environment (e.g., avoiding capturing their roommates' personal items in their videos).

On the other hand, some participants expressed that their learning tasks were repetitive over a certain period of time. Thus, the video data was redundant as they could not identify new patterns through reflection. However, given they still wanted to utilize the video recording feature to help them pay attention to their tasks, some participants opted to live stream their learning process as an alternative to "tracking" without producing redundant data, e.g.,

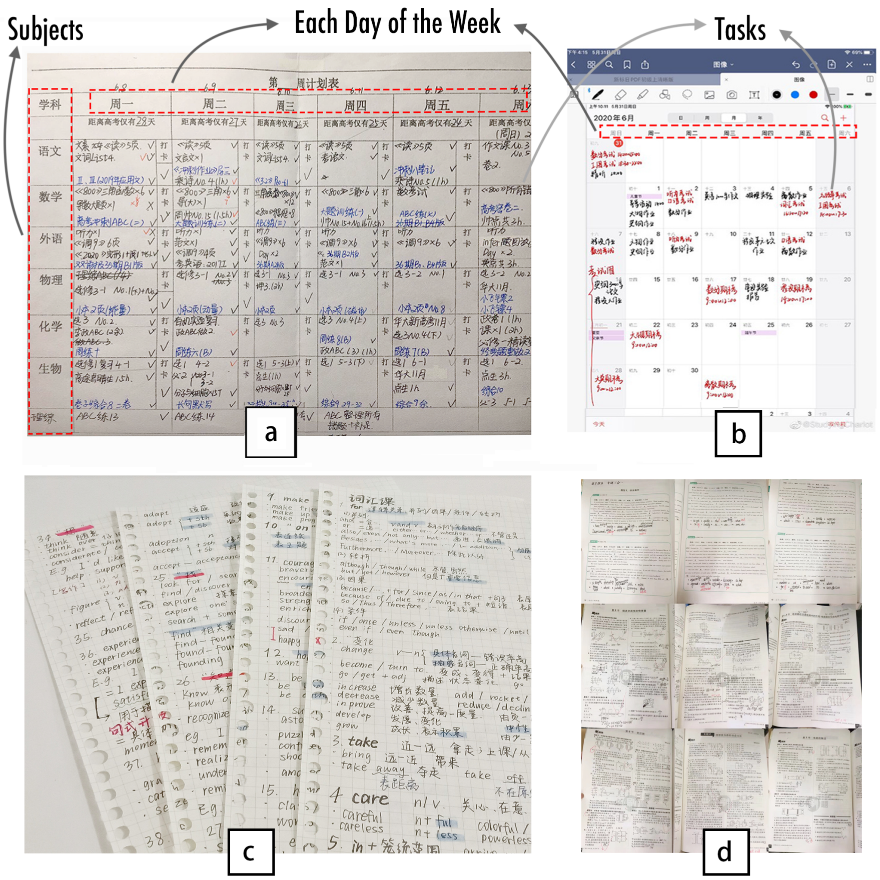


**Figure 2: Learning schedules and learning outcomes tracked by users: (a) Weekly plans on paper, in which users listed the daily tasks for each subject. (b) Monthly plans integrated with calendars, which allowed them to handle monthly tasks and deadlines. (c) Learning notes for the English test that contained English words, their Chinese translations, and related example sentences. (d) Assignments that included modification traces and annotations.**

> *"If my learning tasks for this week are similar, it is meaningless to keep all such videos. I may live stream my study... In this manner, even though no data is being kept, I can still feel like I'm tracking my learning activities and focusing on my tasks."* (P2)

***Duration of Learning Activities.*** Some participants used the timer to measure the duration of their learning tasks (Figure 4). Once the calculation ended, the duration of the time would be displayed on the user's feed. Participants could also view a visual summary of their daily learning time, which included the start and end time of each task and the overall learning time for that day, e.g., *"through looking at a pie chart, it is convenient for me to analyze the learning time spent on different subjects "* (P15). Some participants noted that such visualizations were motivating, e.g., *"I gained a strong sense of achievement"* (P19).

*5.2.3 Learning Outcomes.* When finishing a learning task, participants usually recorded the learning outcomes and posted them in the form of photos, screenshots, or scanned copies, e.g., *"I would take photos of all the items I had done from the papers and workbooks "* (P22). These learning outcomes included (Figure 2): (1) the images of test papers or assignments with modification traces, annotations, information of specific sections, and grades; (2) a summary of completed tasks over a period of time, shown in a single photo with multiple books, papers, and notes; (3) learning notes, such as class notes, article reviews, and error records that were documented in various forms such as mind maps.

Participants noted that they valued the visual effect of these learning outcomes. For example, P8 mentioned that he always made sure that the clarity of learning outcomes' images, e.g.,

> *"I prefer to scan the notes to ensure they are clear enough. I was encouraged to maintain monitoring my learning outcomes by the visual reward of seeing well-organized, high-quality notes."* (P8)

Similarly, the aesthetic attractiveness of well-written notes and neat handwriting was also appreciated by some participants., e.g., *"I would make certain that there is beautiful handwriting and a neat*

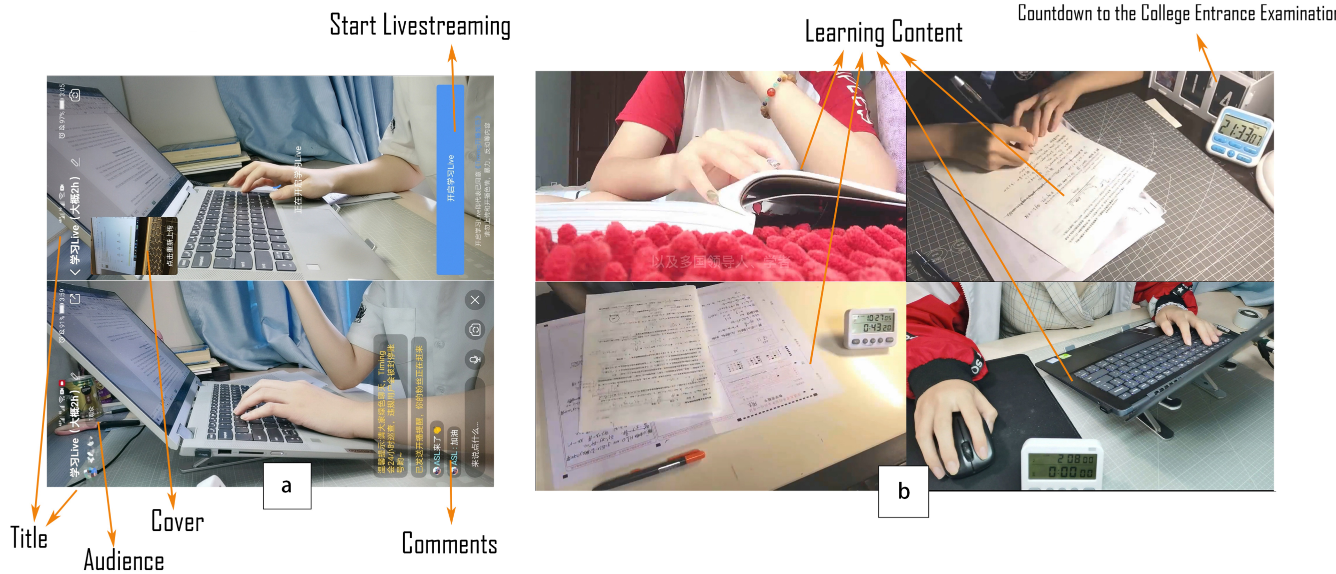


**Figure 3: Video recordings that captured the learning process. (a) Live streams delivered by users; (b) Learning videos recorded by the users. These included learning activities and the surrounding environment.**

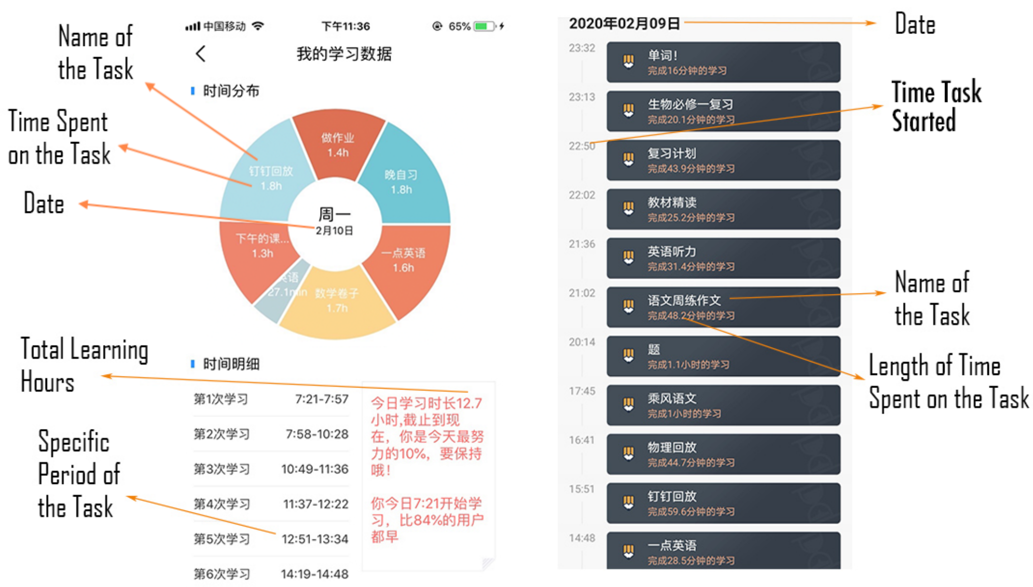


**Figure 4: Duration of Learning Activities. Left: a summary of P15's tasks and corresponding learning duration on February 10th; Right: a record of the names of specific tasks and the amount of time P15 spent on each task.**

*layout... I can't accept that my notes are disorganized"* (P15). Additionally, P22 expressed that she intentionally captured the dense text or thickness of accumulated test paper to showcase her authentic and intuitive learning outcomes, i.e., *"the dense words on the paper or the thickness of piled papers are quite intuitive, creating a great visual impact...demonstrating that I have done a lot of work"* (P22).

*5.2.4 Emotion.* Participants expressed that they would like to document their mood when learning alone because they perceived it to be an indispensable aspect of learning behavior, e.g.,


**Figure 5: Emotion Data: Some participants recorded their emotional states in the task input box using a few words, emojis, or punctuation.**

> *"Emotional state is closely tied to my learning status. For example, if I get things done quickly and well, I'll have a sense of accomplishment and satisfaction."* (P6)

Many users labeled the timer's task names directly after the task content, such as "language practice book chapter 1", or "2019 language paper 3". However, some users used irrelevant words, short sentences, or even an emoji as the task names in the timer, to represent their emotions (Figure 5). Tracking emotions in this way was convenient, e.g., *"it is more troublesome to record my mood with long paragraphs"* (P24), or they felt emotions related to learning state were not appropriate to be shared explicitly, e.g., *"personal emotion is too sensitive to be shared obviously in Timing"* (P23). Tracking emotion in such a manner enabled users to record their fluctuating moods and thoughts conveniently. Participants reported that if they were in a bad mood while studying alone, such as feeling stressed or anxious, they chose to label the task in the timers with their emotions to vent their negative thoughts. P2 noted that, to calm down, she usually logged her annoyances before starting a task, e.g.,

> *"If I am frustrated, I will record that emotion in the timer's task input box. This name conveys a special emotional meaning; for instance, I might name it 'don't be fretful and calm down' to give myself positive psychological hints."* (P2)

Some participants noted that they also used non-text symbols, such as punctuation or emoji, to alleviate their frustration or express their emotions, e.g.,

> *"'!!' means time is running out. I hardly ever use punctuation. If I do, it means I hoped to alleviate stress and anxiety...then get back to work."* (P22)

Interestingly, recording one's negative mood could sometimes lead to amusement. When asked why she logged her emotion as *"I begged myself to do well in a test book about chemical electrolysis cell"*, P24 noted that she was easily distracted while doing an exercise book about chemical electrolysis cells, which made her feel demotivated. However, after documenting such a negative mood, she burst into laughter and found herself in a better emotional state, as she found this recording to be quite amusing, e.g.,

> *"At that moment, I was working on chemistry exercises. Perhaps I was not satisfied with my productivity and felt upset. After logging that emotion, I felt better and burst out laughing, as the name seemed funny."* (P24)

Some participants also noted that when they were in a good mood before starting a new task, they typically logged these emotions in the timer. Doing so could give them an immediate hint that they were doing well and keep working, e.g.,

> *"I typed 'cheer up' in timer and said 'I can do it' to myself. Then breathed in and began to work on exercise*

*books. It felt like a sort of ceremony to start my studying...it helped me stay motivated and focused."* (P22)

## 5.3 Making Sense of Tracked Data (RQ3)

Drawing on the interview data, we found that participants adopted a variety of strategies to make sense of their tracked data in Timing: (1) replaying dynamic and temporal learning videos, (2) glancing through static visual data, (3) migrating between different data while reflecting, and (4) manually recording their summarized reflection to enhance their interpretation of their tracked data.

*5.3.1 Replaying Dynamic and Temporal Learning Videos.* Participants valued the learning videos because the data captured not only their behavior during the learning process but also their surroundings, such as where they were, what content they learned, who was around, and so on. Thus, after recording the videos, participants usually replayed them to gain insights supported by these affluent details.

***Observing learning materials in videos.*** Participants noted that they would pay attention to progress on learning materials (e.g., the number of questions they addressed in textbooks) in the videos, which was perceived as *"the evidence of my learning path"* (P22). Also, reflecting on learning videos provided users with a sense of satisfaction. For instance, P12 felt that observing her textbook being quickly flipped in a replayed video was enjoyable, e.g., *"I thought it would be appealing to see how the book (in the video) was flipped from the first page to the last page and turning thinner and thinner, which was encouraging".*

***Observing learning behaviors in videos.*** When replaying a learning video, participants tended to observe a range of learning behaviors, including gestures and facial expressions, e.g., *"in videos, the shifting gestures are intuitive to be observed ... with attention to gestures, I can easily check and learn about my learning status"* (P2). In addition, participants felt that simply referring to their gestures was insufficient at times. For instance, P24 mentioned that including her face within the camera frame helped her determine whether she had lost focus. She described that facial expressions provided additional insights regarding her attention level, e.g., *"sometimes, I just kept the same gesture ... without capturing my face (via video recording), I couldn't tell if I was thinking or just staring blankly"* (P24). Furthermore, observing mind-wandering behaviors while performing learning tasks allowed participants to reflect on and correct such behaviors in the future, e.g., *"when I checked the videos, I noticed that I always spent time looking for an eraser, a pen, a notebook, or something else when I was doing my homework ... thus, I developed a habit of preparing all the necessary stationery before studying, avoiding being interrupted"* (P22). Alternatively, revisiting learning behaviors in sped-up videos produced a type of "illusion" in which participants worked with high efficiency, e.g., *"(In the sped-up video) I just spent one to two seconds solving the difficult questions"* (P5). This was perceived as encouraging, e.g., *"I felt like a genius in a movie; regardless of how difficult the exercise was, I was able to figure it out in seconds"* (P5). Interestingly, observing motion in the videos might also provide unexpected amusement. Participants reported that some absent-minded behaviors resulted in amusing scenes in the sped-up learning videos, e.g., *"I remembered that I was doing assignments in the morning, during which I ate an apple ... the final video showed I ate it for 3 seconds, which was really surprisingly funny"* (P14).

***Observing one's surroundings in videos.*** Some participants noted that they observed how the environment influenced their learning behaviors since *"a video involves more or less information about the surrounding environment, which is an essential factor influencing my learning productivity"* (P6). Reviewing learning videos also enabled participants to identify factors in the learning environments that were causing distractions. For instance, P14 noticed that *"I took out comic books twice from a pile of books beside me while looking for the books for test preparation".* By reviewing learning videos, three participants reported that people around them could sometimes be a source of distraction, e.g., *"I was continuously interrupted by other people while studying in a café"* (P15). Interestingly, some participants intentionally placed a clock alongside their textbook or computer, which was captured by their phone's front camera. The clock was used to *"assist me to observe how long I could maintain concentration on activities by revisiting my learning video"* (P13).

***Challenges when observing contents in videos.*** Reviewing recorded learning videos also introduced some challenges. For example, due to being sped up, a two-hour-long study session was compressed into a 20-second short video clip, which meant one second in the video would contain six minutes of information if played at normal speed. Therefore, some information, for example, detailed changes in the facial expressions or body gestures, was sometimes hard to observe, e.g., *"it might be challenging to recognize some gestures, for instance, short-term absent-minded behaviors if the videos were compressed from a more than two-hour-long version"* (P8). In addition, some participants felt that they were *"a little confused about which aspect in the video [they] should check and reflect in the first place, such as absent-minded behaviors and learning environments, etc."* (P14).

Overall, to make sense of video data, participants observed behavioral information about themselves and contextual information about their surrounding learning environments in their learning videos. When it came to analyzing behavioral information, participants paid close attention to their gestures and facial expressions. In order to interpret contextual information, participants were attentive to a variety of factors, such as learning materials, desks, locations, and backgrounds.

*5.3.2 Glancing through static, visual data.* When it came to reflecting, participants usually glanced through static, visual data, such as learning schedules, learning outcomes (e.g., completed exercise books), and emotion data. Specifically, participants reported that the photos of learning plans and learning outcomes provided the context to demonstrate their efforts to learn and cope with difficulties. For example, P17 noted that *"glancing through the plans that I successfully completed on my last vacation motivated me to persevere in current learning plans".* Some participants also reported that they pinned the photos of plan sheets or their test papers with poor grades to the top of their posts on Timing, for the sake of providing themselves with a glanceable "warning " in case their minds wandered. Moreover, glancing through the long-term mood data gave rise to a feeling of inspiration. For example, P12 stated that emotion data collected during the period leading up to college entrance examinations not only served as a reminder of how she handled the pressure and challenges she faced while learning alone, but also served as inspiration for her to never give up. Since some emotions were logged as abstract texts, emojis or punctuation, sometimes participants had trouble recalling the meaning of such data, e.g., *" I logged '!!' to represent my feeling during a learning activity, I know it indicates a mood fluctuation, but I am not sure whether it means excitement or annoyance"* (P21).

*5.3.3 Migrating between different data formats while reflecting.* Participants also migrated between different data formats when determining potential factors leading to task failure. Participants reported two motivations behind these sensemaking behaviors. **First, they expressed that though they had scheduled learning tasks, their learning plans lacked sufficient contextual details to facilitate their reflection**, because *"the learning schedule was a brief outline of all tasks assigned to timeframes so it could not reveal how [they] complete the tasks or what [their] emotional states and surrounding context were"* (P2). As a result, in addition to checking her learning schedules about tasks that she failed to complete within the allotted time, P2 reviewed her learning videos to analyze her learning states during that period and determined potential causes for incomplete tasks, such as being absent-minded, stuck with a tricky question or interrupted by another person. On the other hand, P14 preferred to reflect on learning schedules and the images of assignments since she believed that assignments might reveal abundant insights regarding her thought process, such as erasures in the assignments. These concrete details inspired P14 to consider why she was unable to complete a task on time, e.g.,

> *"I wondered why I failed to complete the math paper within 1.5 hours. Thus I referred to the photo of that test paper, in which there were numerous correction marks ....may imply that the cause of the delay was the complexity of exam questions."* (P14)

Moreover, some participants used emotion data as a contextual complement to interpret why they failed to finish tasks, e.g., *"my emotional state frequently fluctuated when I prepared for the final exams thus emotion records helped me to know how I felt and further enabled me to evaluate whether the negative emotions influenced my learning performance"* (P6).

**Secondly, reflecting by migrating between multiple data formats was a way to reassure participants' preliminary assumptions about their learning performance.** Some participants used interruptions recorded in the timer as a reference to confirm their assumptions about concentration levels while completing a particular work in their learning schedule, e.g.,

> *"I failed to finish my physics assignment from 2:00 p.m. to 4:00 p.m. By checking the timer record, I found that the calculation of learning duration was interrupted seven times, each lasting only for four to six minutes. The records helped me to locate when the interruption occurred, and further, I could figure out what the interruption was. "* (P13)

Also, P21 expressed that both the learning videos and learning outcomes could offer in-depth information on a particular task. Her hypothesis about whether her mind was wandering while learning was effectively validated by migrating from learning videos to learning outcomes, e.g.,

> *"From the video that documented the process of working on a physics paper, I found that I spent too much time addressing a particular question. Then I referred to the photos of the paper to assess how challenging the relevant task was. The fact that it was a simple question, and it should have been solved quickly... indicated that I might most likely zone out at that time."* (P21)

To validate their guesses about emotions at a specific moment, some participants preferred to migrate from emotion data to learning videos, given that the actions in the videos could naturally demonstrate their emotional states, e.g., *"I could not recall whether I felt upset even if I typed "frustration" in the task input box of the timer...so I replayed the corresponding learning videos and tried to look for some cues and found that I frequently grabbed my hair and drew many circles on scratch paper, and rarely worked on my homework."* (P2) Alternatively, some participants migrated from the emotion data to the associated time duration on the timer as an implicit way to validate their hypotheses about how their emotional states changed, e.g., *"once, I noticed a record "calm down and never give up" in the task input box of the timer, which meant I must be restless at the beginning then I found that the associated time duration lasted for 1.5 hours, indicating that I might calm myself down gradually"*(P7).

*5.3.4 Manually recording insights after reflection on multiple data sources to enhance interpretation.* Participants usually manually recorded their insights in the form of text after reflecting on different data in Timing, as a manner to enhance their interpretations. Manually logging reflections was perceived to be *"a process of re-examining the findings and making the insights clearer"* (P2). This method also had benefits in terms of easing the burden of reviewing for a second time, e.g.,

> *"Repeating the reflection was burdensome. If I have already recorded the integrated insights, such as additional plans and strategies to improve performance, I do not need to reflect again. Instead, I only need to rapidly scan what I have documented."* (P24)

However, given multiple formats of tracked data, integrating various insights from reflections was found to be complicated, e.g.,*"reflection based on learning data is a complex process. I frequently interpret multiple types of data to comprehend my learning performance. I must integrate insights from several data sources, which is a complicated thinking and reasoning process "* (P2).

## 6 DISCUSSION

In this section, we describe how non-classroom and non-computer-based tracking and reflection behaviors support self-directed learning, the value of qualitative data in this context, and design suggestions about how to better support non-classroom and non-computer-based learning tracking activities in terms of (1) supporting emotion data recording and recall, (2) balancing learning process capture and privacy concerns, (3) assisting interpretation of dynamic and temporal learning videos, and (4) lowering the burden of comprehensive reflections with multiple data sources.

## 6.1 How Personal Learning Data Tracking Practices Supported Self-Directed Learning

We discuss how personal learning data tracking behaviors on Timing supported self-directed learning in non-classroom and non-computer-based contexts from the following aspects: how timing usage mirrored SDL model, how qualitative and quantitative data tracking both supported self-directed learning, unique aspects of data tracking practices and potential reasons for these unique behaviors.

*6.1.1 Timing Usage Mirrored the SDL Model.* Our research extended previous research about how automatic learning tracking systems enabled self-directed learning [31, 35–37, 63, 70], by revealing how students tracked and reflected on their non-classroom and non-computer-based learning activities. We found that Timing users proactively developed learning schedules, monitored learning states, and reflected on learning performance through self-tracking via three phases of self-directed learning that mirrored Costa and Kallick's SDL model [18].

In the first phase, **self-managing**, learners were able to be aware of the workload, necessary information, and results of learning tasks and making use of previous knowledge. In the context of learning tracking with Timing, when participants realized that they lacked the motivation to continue learning tasks, they opted to take a quick look at their previous learning recordings (e.g., photos of assignments and emotional states) to encourage themselves. Frequently checking their pre-recorded learning tasks on their schedule enabled participants to keep track of their workload and manage their outcomes when completing a task.

In the second phase, **self-monitoring**, learners assessed their learning performance using cognitive and metacognitive strategies and were aware of other effective strategies. In our work, participants used video recording as an immediate way to monitor whether they focused on their tasks since participants could glance at their phone's screen to be aware of their real-time learning behavior. Recording learning videos also prevented users from being distracted by their mobile phones because the application needed to remain in the foreground to continue recording.

Lastly, in the third phase, **self-modifying**, learners evaluated and made sense of their prior experiences while making plans about future learning tasks. Our findings showed that participants migrated across different tracked data to evaluate their performance on different learning tasks. Such a sense-making method assisted participants in metacognitively analyzing their learning state. As the Educational Endowment Foundation report [26] indicates, metacognition is one of the most crucial and powerful learning skills that enables students to determine their strengths and weaknesses and eventually improve their learning. Overall, these tracking practices demonstrated how self-tracking using Time was a novel way of facilitating self-directed learning and metacognition.

*6.1.2 Qualitative and Quantitative Data Tracking Both Support Self-Directed Learning.* Prior research on learning tracking tools focused on automatically tracking computer-based learning activities such as the frequency of social interactions, time expenditure, course content usage, and academic performance [53, 67]. Our findings extended this line of work by revealing the types of learning data students tracked and how they made sense of non-computer-based learning activity data. Our participants reported that in addition to tracking the amount of time spent on learning tasks, they also tracked a range of qualitative data, including learning process videos, images of learning outcomes, and emotions. Prior research demonstrated that qualitative data, such as photos [11, 12, 16, 27], text [4, 50], and videos [66], could provide rich details to support experience recall and reflection. Although this prior research investigated the value of qualitative tracking data, little was known about its application to non-computer-based self-directed learning.

Our study revealed the value of qualitative capture. Participants constantly migrated from quantitative data (i.e., time spent on learning tasks) to qualitative data (e.g., learning process captures by videos). Quantitative data about learning schedules guided participants to execute tasks according to a pre-defined schedule. Such data could also enable participants to obtain basic, raw knowledge about task completion. However, when participants intended to reflect further on quantitative data to determine the factors leading to their failure to complete tasks, the quantitative tracking could not fulfill their needs. For instance, prior research demonstrated that it was challenging for users to recall the details behind the numeric data [40]. **We argue that for non-computer-based learning activities, qualitative and quantitative learning data are complementary and allow for more holistic tracking and reflection activities.** Quantitative tracking provided a basic overview in terms of productivity, while qualitative capture offered rich contextual details to help participants further interpret their data. Through reflecting about the qualitative capture, participants could be aware of the detailed learning content of a specific task, how they executed the tasks, with whom they completed the tasks, and the context surrounding the tasks. Making sense of such qualitative data enabled participants to make decisions about which aspects of learning behavior (e.g., attention and emotion) should be adjusted in the future.

We identified some reasons that may lead participants to value qualitative data. One of these reasons may be the inherently iconic features of the tracked data, such as photos of learning outcomes, learning videos, and emojis (as emotion data). Compared to symbolic data (e.g., the visualization of time), iconic data is easier to interpret. Participants did not have to perform further data curation before interpretation. Another reason might be that manually captured data contained direct and intuitive contextual evidence supporting participants' data reasoning. Instead of trying to recall the context of data collection (e.g., the weather at the time of data collection), having some record of the data collection process at hand might enable a more efficient and convenient sensemaking practice. These reasons may also explain why our participants were not found to hide, remove, or perform additional annotations on their data segments and why they were not found to recall contextual information about data, which contrasted with findings reported in Coşkun & Karahanoğlu's work [17].

*6.1.3 Tracking and Sensemaking Behaviors Informed By Pressure.* While prior work, such as Rooksby et al. [56]'s lived informatics model, and Potapov et al.'s sensemaking with teenagers [54] described self-tracking as intermittent and improvised, we found tracking behaviors on Timing to be continuous and persistent. Participants not only tracked data types that were complex and full of details (e.g., learning output photos, learning process videos, emotions) but also made sense of the data in a systematic and rationale-driven manner (e.g., migrating between different data types to determine which factors led to distraction). The inherently high-stake attributes [57] of the exams that most participants were preparing for may explain the above distinctions.

In particular, the majority of participants in our study used Timing while preparing for their National College Entrance Exams (NCEE) or the national entrance examination for postgraduates. The pressure of these high-stake exams may drive students to persistently capture and reason about as many diverse types of perceived meaningful data as they could. Participants mentioned that they intend to *"holistically and systematically assess learning states to diagnose factors that are perceived to negatively affect learning performance, and prepare well for such a prospect-affecting exam"* (P2). As for their ability to utilize the multiple features of Timing, being exposed to a variety of emerging technologies (e.g., mobile phones, computers, internet, etc.) during teenagers' maturation may help explain such behaviors [71].

Furthermore, while prior work [11] indicated that social aspects of tracking applications could bring benefits (e.g., emotional support and motivation), some participants in our study did not appreciate Timing's social features. Personal learning data tracking practices under pressure might help explain such perceptions. First, given the pressure on exam preparation, efficiency was perceived to be essential. Thus, being distracted by any social function (e.g., other users' posts) would perhaps be perceived to disrupt participants' learning schedules and be time-wasting. Second, viewing other users' posts might put some users under extra pressure, which led them to feel overwhelmed and ultimately abandon Timing.

## 6.2 Design Implications to Support Non-classroom and Non-computer-based Learning Tracking Activities

Based on our findings, we provided design suggestions for supporting emotion data recording and recall, balancing learning process capture and privacy concerns, assisting interpretation of dynamic and temporal learning videos, and lowering the burden of comprehensive reflections with multiple data sources.

*6.2.1 Design to Support Emotion Data Recording and Recall.* One unexpected qualitative tracking behavior was that, though there was no function in Timing that supported capturing emotions, many participants took the initiative to implicitly record their emotional states during a learning activity in the task input box (Fig.5) using a few words, emoji, or punctuation. This behavior enabled participants to reflect on their emotions, thoughts, and feelings for a learning task, however, since the format was somewhat abstract, some participants noted that they could not remember what the emotions or feelings were for some tasks. This raises an interesting question about how to design interfaces to better support the capture of emotions or feelings. It may not be appropriate to add an additional function named "emotion tracking", since all data users tracked were public. Thus, designers may take users' personalities or perceptions of privacy for learning data into consideration when designing this feature.

*6.2.2 Design to Balance Learning Process Capture and Privacy Concerns.* Our findings extended prior work on time management and planning [49] by revealing that, beyond scheduling and reviewing tasks in software (i.e., note apps) and paper-based tools (i.e., notebooks), video was a useful medium for recording specific task execution process. Recording learning process videos enabled participants to concentrate on tasks because they felt monitored, while making sense of learning video data provided contextual information to help them quickly determine why they were distracted. Some participants, however, expressed privacy concerns about recording their learning process, especially college students who self-studied in dormitories where it was inevitable that roommates would be in the video frame. As a result, they struggled to capture necessary content (e.g. textbooks, upper bodies, or the computer screens) while ensuring the privacy of those in their environment.

Prior work has suggested several methods that could potentially mitigate privacy concerns, such as limiting the capture of sensitive data (e.g., location and audio) [1], making the data appear abstract [22, 25, 28], disabling specific functions [2], or abandoning the use of trackers [23]. When designing personal learning data tracking tools that include video recording features, designers may also consider implementing functions that allow users to control the types of sensitive information that could be automatically selected and filtered during the recording process.

*6.2.3 Design to Assist Interpretation of Dynamic and Temporal Learning Videos.* Our study found that interpreting sped-up video data was challenging because it was difficult to identify whether participants were focusing or staring blankly when they were not writing or flipping the pages. We also found that condensing learning videos from two or more hours down to 20 to 30 seconds sometimes led to participants failing to notice short-term behavior. To address such challenges, it may be useful to enable users to select particular sections of a sped-up clip and slow down the play speed or allow the user to select the duration of the sped-up clip they wish to be generated. It is also possible to utilize computer vision techniques to capture and classify the gestures and facial expressions in a video, such as extracting those moments when a user is zoning out and annotating them on the video timeline for easy navigation.

*6.2.4 Design for Integrative Reflection with Multiple Data Sources.* Instead of simply being aware of the current learning states in their mind and taking action to adjust them, participants preferred manually recording what they obtained from the reflection due to the complexity of the multiple sources of tracked data they were consulting. As obtaining insights from interpreting multiple sources was challenging, participants usually manually recorded such insights after holistically reviewing the data they tracked, however, it was inevitable that they forgot some details. Previous research [40] has demonstrated that it could be useful to offer hints to help users recall details about the data, thus, personal learning data tracking applications should include features that prompt users to immediately record their insights using text or audio forms. Such features may help users organize and record their holistic insights while interpreting multimodal data, however, it should be mindful of data collection burden that this feature may impose on users.

# 7 LIMITATIONS AND FUTURE WORK

Our research investigated Chinese students' personal learning data tracking and sensemaking behaviors on Timing. The persistent tracking and intense sensemaking behaviors may be unique to Chinese students, given that the high-stake exams participants were preparing for can significantly impact their tracking motivations and behaviors. It would be interesting to verify whether our findings could be applied to self-directed learning in other cultures. For example, some previous research has indicated that similar patterns of learning and tracking might happen among students in Korea and Japan as well [20, 69]. Also, given most of our participants were middle school or college students, they might not be representative of a broader pool of Timing users. Future work may explore tracking practices of participants with diverse ages and occupations (e.g., non-student learners). Further, our work primarily focused on tracking behaviors on Timing. Future research may look into whether other learning-tracking applications may reveal different insights.

# 8 CONCLUSION

Previous learning tracking systems mainly focused on tracking group-based learning data on computers. Little was known, however, about how such trackers should be designed to capture non-computer-based learning activities and what types of learning data were personally meaningful for students. We reported on a qualitative study with 24 users of Timing, a learning tracking application in China. We found that users predominantly tracked a variety of qualitative learning processes in addition to capturing quantitative data. Participants migrated between different tracked data and manually recorded their summarized insights during sensemaking. Our findings indicated that integrating multimodal and qualitative learning data tracking in personal learning data tracking tools could support self-directed learning in non-classroom and non-computer-based contexts. Further, we provided design suggestions for supporting emotion data recording and recall, balancing the learning process capture and privacy concerns, assisting interpretation of dynamic and temporal learning videos, and lowering the burden of comprehensive reflections with multiple data sources.

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