Impacts of Accountability Partners on Users' Online Learning Behaviors

Xiaohui Zhang
University of Wisconsin-Milwaukee
xhzhang@uwm.edu

Amin Sabzehzar
Tulane University
asabzehzar@tulane.edu

Tongxin Zhou
Arizona State University
tongxin.zhou@asu.edu

Hong Guo
Arizona State University
hguo@asu.edu

Abstract

Online Learning Platforms (OLPs) are rapidly expanding, yet users of OLPs face high dropout rates due to social isolation and lack of motivation. Accountability partnership, where users communicate and monitor each other's learning progress, is an emerging feature that OLPs incorporated to address the setbacks. This study investigates the impacts of accountability partnerships on OLP users' learning behaviors. Analyzing data from Shanbay, an English learning platform in China, we show that accountability partnerships have dual effects on users. On the one hand, having an accountability partner increases users' check-ins on OLPs. On the other hand, users with accountability partners decrease their actual study time and show more pretending-to-study behaviors on OLPs. Additionally, we demonstrate that communications among partners and the personal goals of individuals enhance the positive effect (increased check-ins) of accountability partnerships while mitigating the negative effects (reduced study time and more pretending behaviors). These insights underscore the dual-edged nature of accountability in online learning, highlighting both its motivational benefits and potential pitfalls.

Keywords: Accountability Partnerships, Online Learning Platforms, Learning Behaviors, Extrinsic Motivation, Intrinsic Motivation

1. Introduction

Online learning platforms (OLP) have become popular by providing learners with convenient and affordable access to knowledge (Santhanam et al. 2008). Although these platforms are expected to expand exponentially, reaching over $370 billion by 2026, they frequently experience high dropout rates and suboptimal learning outcomes among learners (Huang et al. 2023). The lack of peer support and collaboration limits learners' motivation and performance, which is one of the key factors contributing to these setbacks (Richardson et al. 2017). To mitigate this issue, OLPs have integrated social features into their platforms to encourage mutual support and motivation. For instance, Coursera offers discussion forums, enabling interactions among course-mates, and Duolingo and Shanbay (Chinese version of Duolingo) launched the Friends Quests (Deskmate) feature, where learners team up to learn together. In these setups, learners become learning accountability partners, through which they mutually observe and report their learning progress to each other (Sedikides et al. 2002).

While accountability partnerships in OLPs offer certain advantages, the overall benefits and potential side effects are not yet fully understood. Accountability partnerships enhance learning behaviors by enabling learners to observe each other and establish norms based on shared goals (Li et al. 2021; Wu et al. 2023). Additionally, being part of a team helps learners stay more motivated to achieve their learning objectives (Kou and Stewart 2018). However, having an accountability partner can lead to unintended consequences, such as shifting the emphasis from genuine learning to merely tracking and reporting progress. Accountability partnerships often emphasize observable aspects of the learning process, such as daily task completion, which partners can easily monitor. In contrast, actual learning efforts, like the time spent studying and depth of understanding, are harder or impossible for partners to observe (Lerner and Tetlock 1999). Therefore, to seek social approval or avoid disapproval, learners with accountability partners may prioritize appearances over genuine learning. As a result, individuals might engage superficially to meet minimum social expectations, potentially hindering real educational progress. This issue is particularly

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significant in online settings due to the lack of physical monitoring.

Considering these potential benefits and limitations, we aim to study the effects of having accountability partnerships on individuals' learning behaviors and the contextual characteristics that determine the viability of such partnerships. Regarding contextual characteristics, we focus on communication among partners and the personal goals of individuals. Formally, we address the following research questions in this study:

RQ1. *How does having an accountability partner on OLP influence a user's learning behaviors?*

RQ2. *How does communication among partners and the personal goals of individuals affect the impacts of accountability partnerships on learning behaviors?*

We theoretically analyze the research questions by examining the distinctions and interactions between intrinsic and extrinsic motivation in the presence of accountability partners (Lepper and Henderlong 2000). Intrinsic motivation involves engaging in an activity for its inherent satisfaction, finding it exciting and enjoyable. In contrast, extrinsic motivation is driven by the desire to achieve an external goal, such as earning a reward or avoiding punishment. Applying this to accountability partnerships, we argue that having an accountability partner creates explicit stimuli that enhance a user's extrinsic motivation and can change the user's learning behaviors. Furthermore, we explore the boundary conditions under which accountability partners can maintain a high level of intrinsic motivation while benefiting from increased extrinsic motivation. Specifically, the factors we study here are communication and personal goals.

We collected data from Shanbay to empirically answer the research questions. Shanbay facilitates accountability partnerships through the deskmate feature. In a deskmate relationship, two users can monitor each other's study progress and work together to maintain the relationship and earn rewards like badges or tokens. Our dataset includes the daily study records, including daily check-ins, time spent studying on the platform, and the deskmate status of 158,778 users from their registration date. Section 3 provides detailed information about our research context and data. We employ empirical methods, including difference-in-difference, matching, instrumental variable, and counterfactual estimator, to identify the impacts of having an accountability partner on a user's learning behaviors.

The empirical findings suggest that having an accountability partner increases a user's likelihood of check-in (i.e., performing at least minimum learning requirements) on the platform to maintain the partnership relationship. However, conditional on check-in, a user with an accountability partner spends less time studying. Accountability partners also increase the probability of cheating (a condition when users pretend to study). Together, these results suggest that deskmate relationships result in learners exhibiting a higher level of extrinsically motivated learning behavior, as evidenced by more platform check-ins but less time spent on actual learning and more cheating behavior. Regarding the conditions that facilitate effective learning behaviors, we find that communication (e.g., through WeChat) and the learners' personal goals (e.g., whether learners have scheduled exams) act as motivational stimuli that amplify the benefits of the deskmate relationship, increasing study propensity and time spent while decreasing pretending behavior. These findings contribute to IS literature by looking at the impacts of accountability partners, an emerging social feature on online learning platforms. We also provide feedback to research on accountability by documenting the unintended negative consequences of accountability in the online setting.

2. Related Literature and Hypothesis Development

2.1. Online Learning and Platform Designs

Online learning, also known as technology-mediated learning or e-learning, enables individuals to acquire knowledge conveniently via information technology platforms (Alavi and Leidner 2001). Research has documented its advantages, such as convenience, low cost, and personalization (Leung et al. 2023; Zhang et al. 2004). However, it is also a common fact that learners often face a high quit ratio and less desirable learning performance in online learning environments (Baek and Shore 2016; Michinov et al. 2011). Prior studies record a comprehensive set of factors determining the effectiveness of online learning platforms, including user characteristics, learning context, system design, etc. (Gupta and Bostrom 2009). Research shows that most undesirable outcomes of online learning could be attributed to users' low self-control (Santhanam et al. 2008), lack of peer support (Richardson et al. 2017), and absence of monitoring (Huang et al. 2021).

To overcome the shortcomings of online learning, a large strand of empirical research investigates various designs and strategies that aim to improve the performance of online learning. From the system design perspective, studies show that well-designed gamification elements like competitions, badges, and leaderboards can effectively promote online learning

performance (Gibson et al. 2015; Santhanam et al. 2016). More closely related to this research, a series of studies investigate the impacts of social features on people's online learning behaviors. Incorporating social features like social networks and forums can effectively enhance users' learning activities on OLPs by increasing idea elaboration (Narang et al. 2022). Li et al. (2021) reveal that disclosing peer performance can effectively boost individuals' learning efforts in competitive online environments. Similar effects of pure social presence are also observed in nonmandatory online learning contexts (Zhang et al. 2024). Compared to previous research, this study distinguishes itself by examining a social feature where individuals are not only aware of and interact with each other but also justify and take responsibility for one another. Additionally, we are among the first to investigate users' cheating behaviors, a critical but often neglected online learning behavior.

2.2. Accountability Partnership

Accountability is a widely used term in law, business, and healthcare domains; it refers to the implicit or explicit expectation that one may be called on to justify her/his actions to others (Lerner and Tetlock 1999). Accountability partners describe a relationship where two individuals agree to support each other and take each other's responsibilities as their own obligations (Kou and Stewart 2018). The concept is widely adopted in various settings to improve individual or organizational performance, such as management decision quality (Dalla Via et al. 2019), pursuing health goals (Gershon et al. 2024), and encouraging IT adoption (Cornell et al. 2011). In education, accountability partners in study buddy or peer coaching formats have also been proven effective in improving students' learning performance (Thalluri et al. 2014). However, most previous studies on accountability partners concentrated in offline settings, where physical monitoring is available. In the online environment, the truthfulness of accountability partners' justifications to each other is not easily guaranteed. This study fills in this gap by examining the effects of accountability partners in online learning platforms.

2.3. Hypothesis Development

Having an accountability partner on OLPs can subtly influence users' motivations and, consequently, their learning outcomes (Lepper and Henderlong 2000). Accountability partners are rooted in social accountability, where individuals commit to mutual oversight of progress towards shared goals. Knowing that someone else shares the same goals and faces similar challenges can make the learning experience more enjoyable and less isolating (Gershon et al. 2024). More importantly, social accountability invokes the desire for social approval or the fear of social disapproval. When individuals fail to meet others' expectations, they often experience feelings of guilt (Zhang et al. 2024). This serves as a strong extrinsic motivator, compelling individuals to dedicate themselves to the learning process. While extrinsic motivation can effectively drive regular participation, it often emphasizes compliance over genuine engagements (Deci and Ryan 2013), which can lead to superficial learning behaviors rather than deep, meaningful ones.

Given this extrinsic motivation, users are potentially less driven by an inherent interest in the learning material (intrinsic motivation) and more by the desire to maintain social connections or avoid the negative consequences of losing them. This scenario may lead to increased engagement metrics like whether study (*easy* to be observed by the partner), but not necessarily more time spent learning (*hard* to be observed by the partner). This behavior could also lead to increased instances of cheating, where learners feign learning to meet the expected metrics without actually engaging with the learning material. Therefore, we hypothesize:

H1: *Accountability partnerships lead to* ***(a)*** *an increase in the probability of studying (CheckIn) but* ***(b)*** *a decrease in the actual time spent learning (TotalStudyTime) and* ***(c)*** *an increase in cheating behaviors (PretendingStudy).*

Communication is a determinant of the effectiveness of accountability partners on OLPs (Lerner and Tetlock 1999). First, communications between accountability partners increase the sense of monitoring, alleviating the overfocus on mere process reports and reminding users to put in genuine efforts (Liang et al. 2024). Second, through communication, users can offer encouragement and send reminders to their partners. This allows them to foster a sense of connection and belonging. The enhanced sense of relatedness with their peers makes individuals feel valued and supported throughout the learning process, thereby strengthening their personal learning efforts (Wu et al. 2023). Thus, we hypothesize that:

H2: *Communication* ***(a)*** *enlarges the lifting of study probability (CheckIn),* ***(b)*** *alleviates the reduction of study time (TotalStudyTime), and* ***(c)*** *alleviates the lifting of cheating behaviors (PretendingStudy), when having accountability partners.*

Personal goals can make individuals focus effort and attention on relevant activities while minimizing engagement in unrelated tasks (Santhanam et al. 2008). Users with personal goals can stay intrinsically focused on the learning process without sacrificing outcome-

motivated learning. This intrinsic motivation, when combined with the extrinsic motivation provided by external accountability, pushes learners to stay on track, i.e., continue the learning process (CheckIn). At the same time, learners with goals boost their outcome-motivated learning by increasing learning efforts (TotalStudyTime) and reducing the likelihood of cheating (PretendingStudy). With that, we hypothesize that:

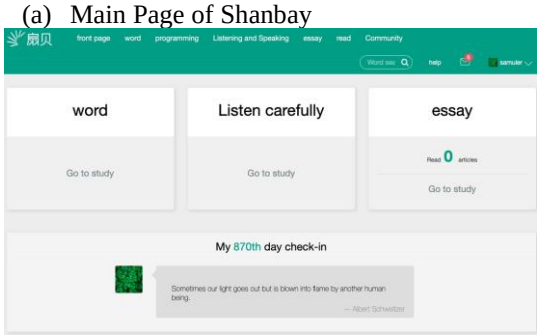
H3: *Personal goals* ***(a)*** *enlarge the lifting of study probability (CheckIn),* ***(b)*** *alleviate the reduction of study time (TotalStudyTime), and* ***(c)*** *alleviate the lifting of cheating behaviors (PretendingStudy), when having accountability partners.*

3. Research Context and Data

3.1. Shanbay and Deskmate

We empirically test our hypotheses regarding accountability partners in the context of Shanbay, leveraging its deskmate feature. Shanbay is one of the top online learning platforms in China. By the end of 2023, Shanbay had around 1.5 million monthly active users. It helps users learn English by memorizing words (via browsing flash cards), reading passages, and listening to conversations. Figure 1(a) illustrates Shanbay's main page. Shanbay labels a user as checked-in once the user has finished a minimum amount of learning tasks (twenty words, two passages, or five conversations) on a date. Each user's check-in records are publicly observable. While the learning time is not observable on Shanbay (or by the accountability partner), its API recorded the actual learning time. Shanbay offers a feature named 'Deskmate' to help users form accountability partners. Figure 1(b) displays the policy page of Deskmate. Users within a deskmate relationship can observe each other's study records, send each other encouraging emojis, and remind each other to study. Figure 1(c) illustrates the interface of the deskmate feature. Shanbay API records each user's history of deskmate relationships.

(a) Main Page of Shanbay



(b) Deskmate Feature on Shanbay

Translation: What is a deskmate? A deskmate is the one who virtually sits by you. On Shanbay, becoming deskmates represents an obligation to study together. You will be monitored and reminded when you forget to check in (learn). Here, people encourage each other. **How to join a deskmate relationship?** You can invite your friends or apply to other Shanbay users (via matching systems). **How to maintain a deskmate relationship?** The relationship continues as long as two users keep checking in continuously and no one abandons the other. If the relationship ends due to the breaking of check-in, two users can choose to continue the deskmate relationship.

(c) Deskmate Feature on Shanbay

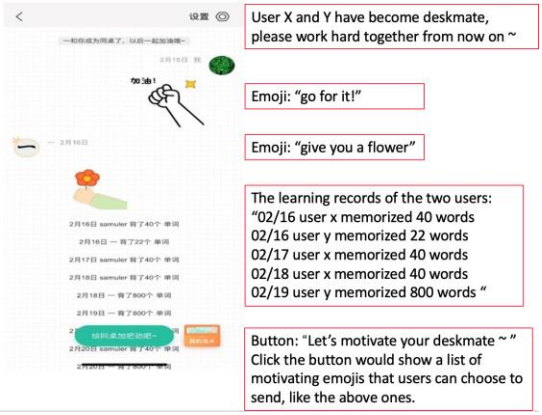


Figure 1. Illustrations of Shanbay and Deskmate Features

3.2. Data

We construct a panel dataset at the user-date level. The original sample, generated from a random snowballing process, contains 158,778 users (124,247 of whom had at least one deskmate experience, and the remaining 34,531 did not have any). We collected their basic user information, complete study records, and deskmate histories, ranging from their registration date

to 11/10/2023. Then, we applied the coarsened exact matching (CEM) method to construct a sample where users with/without deskmate experience are similar to each other. Specifically, we conducted the matching process based on a comprehensive set of user labels (57 labels) about their language proficiency exams (e.g., IELTS, GRE, or CET-4), academic/professional focus (e.g., academic writing, business English), general language skills (e.g., improve listening/reading, expanding vocabulary), education status (e.g., college students, employed), personal goals and study habits. The matched sample overall contains 87,752 users (53,311 users with deskmate experience and 34,441 users without), with 124,387,402 user-day observations. To narrow down our dataset to active users, we restrict the dataset to active periods (defined as having at least one study record in a time window of 4 months, i.e., two months before and after). Thus, we get a dataset with 62,811,619 observations. There are 194,796 deskmate sessions in this sample.

The key independent variable in this study is a user i's status of whether having a deskmate on a date t ($WithDeskmate_{it}$). For learning behaviors, we first measure the user's engagement with learning on date t through study records ($CheckIn_{it}$). To measure user i's learning efforts on date t, we use the total time (in seconds) the user spent on Shanbay ($TotalStudyTime_{it}$). We determine cheating behaviors, i.e., aim for check-in without actual learning, through the following method. We calculate the average time that a user spends on memorizing each word. If a user spends less than 0.5 seconds on each word, we label the corresponding learning record as pretending ($PretendingStudy_{it}$). Our results hold with different thresholds and methods to determine cheating/pretending behaviors. To further control potential biases caused by study momentum, we also calculated each user's long ($UserStudyDays_{it}$) and short ($PreviousWeekStudyTime_{it}$) study accumulations. The summary statistics of key variables are reported in Table 1.

Table 1. Variable Definition and Summary Statistics

Variable and Definition	N	Mean	SD	Min	Max
$WithDeskmate_{it}$ Dummy variable: 1 if user i is in a deskmate relationship on date t and 0 otherwise.	62,816,619	0.122	0.327	0	1
$CheckIn_{it}$ Dummy variable: 1 if user i has a study record on date t and 0 otherwise.	62,816,619	0.444	0.497	0	1
$TotalStudyTime_{it}$ The time length (seconds) of user i's study record on date t.	27,893,348	857.607	21,051.550	0	33,782
$PretendingStudy_{it}$ Dummy variable: 1 if user i's study record on date t is determined to be pretending study.	19,384,734	0.022	0.147	0	1
$UserStudyDays_{it}$ The cumulative days that use i studied on the platform by date t.	62,816,619	400.233	578.546	0	4,519
$PreviousWeekStudyTime_{it}$ The time length (seconds) of user i's study records in the week before date t. (Log-transformed)	62,816,619	4.479	4.328	0	22.880

4. Empirical Method and Results

4.1. Empirical Method

To test our hypotheses, we rely on our panel data and leverage users' deskmate experience on Shanbay to construct a difference-in-differences (DID) design. We estimate the effects with two-way fixed effect models. We include individual fixed effects and date fixed effects to account for any user-specific unobservable factors and any platform-wide temporal effects. We also control the study momentums (user-time variant). Equation (1) below is our main regression specification:

$$Y_{it} = \nu_i + \beta_1 \cdot WithDeskmate_{it} + \gamma' \mathbf{Z}_{it} + \mu_t + \varepsilon_{it}, \quad (1)$$

where ν_i are user fixed effects and μ_t are date fixed effects. The coefficient β_1 captures the effects of our interest on the outcome variable Y_{it}. Our main outcome variables are the three sets of learning behaviors ($CheckIn_{it}$, $TotalStudyTime_{it}$, and $PretendingStudy_{it}$). $\mathbf{Z}_{it}$ is the vector of time-variant control variables ($UserStudyDays_{it}$ and $PreviousWeekStudyTime_{it}$). To test the moderating effects proposed in H2, H3, and H4, we revise the specification as Equation (2) below:

$$Y_{it} = \nu_i + \beta_1 \cdot WithDeskmate_{it} \cdot \text{Moderator}_i + \beta_2 \cdot WithDeskmate_{it} + \gamma' \mathbf{Z}_{it} + \mu_t + \varepsilon_{it}. \quad (2)$$

where $Moderator_i$ can be measures of communication and personal goals. The coefficient β_1 captures the moderating effects of interest.

Several endogeneity issues could bias our empirical estimations. First, to address the confounding issue arising from different attributes between users with and without deskmates, we conduct matching when constructing the dataset, ensuring users are comparable across a comprehensive set of attributes. Second, to tackle self-selection bias—the possibility that users self-select into deskmate relationships—we construct an alternative sample for robustness checks, leveraging the exogenous shock that occurs when a user is forced out of a deskmate relationship due to the other user abandoning them. Further, we adopt two

alternative identification strategies (instrumental variables and counterfactual estimators) in robustness checks. All these analyses confirm our main findings.

4.2. Empirical Results

Table 2 reports the impacts of having a deskmate on learners' check-in. Columns (1), (2), and (3) report results estimated using OLS (linear probit), Probit, and Logit models. All coefficients are positive and significant, indicating that users are more likely to engage with the platform when having a deskmate. Taking the OLS model for interpretation (the highlighted cell), we see that after having a deskmate, a user is more likely to engage by 43.4% compared to not having a deskmate. Thus, our H1(a) is supported; accountability partners increase check-in.

Table 2. Deskmate's Effects on CheckIn

DV:	$CheckIn_{it}$		
	(1) Linear Probit (OLS)	(2) Probit	(3) Logit
$WithDeskmate_{it}$	0.434***	1.815***	3.246***
	(0.002)	(0.007)	(0.013)
User FE	Y	Y	Y
Date FE	Y	Y	Y
No. Observations	62,816,619	62,816,619	62,816,619
R2 / Pseudo R2	0.455	0.408	0.409
Notes: Robust standard errors are clustered at the user level. *p < .1; **p < .05; ***p < .01			

Table 3 reports the impacts of having a deskmate on users' learning efforts ($TotalStudyTime_{it}$) conditional on whether they studied. To alleviate concerns about biases due to outliers, we report the results of log-transformed and winsorized (95%) study time in Columns (2) and (3). All coefficients are negative and significant, suggesting that learners spend less time on the platforms when having a deskmate. Based on Column (3), having a deskmate makes a user study less by around 72 seconds (i.e., 8.4% of the average study time of 857 seconds). These results support our H1(b) that having an accountability partner decreases a user's actual learning time.

Table 3. Deskmate's Effect on TotalStudyTime

DV:	$TotalStudyTime_{it}$	$Log(TotalStudyTime_{it})$	$Winsorize(TotalStudyTime_{it})$
	(1) OLS	(2) OLS	(3) OLS
$WithDeskmate_{it}$	-5084.35**	-0.021***	-72.146***
	(2261.45)	(0.006)	(22.535)
User FE	Y	Y	Y
Date FE	Y	Y	Y
No. Observations	27,893,348	27,893,348	27,893,348
R2	0.0002	0.411	0.051
Notes: Robust standard errors are clustered at the user level. *p < .1; **p < .05; ***p < .01			

While it is possible that the observed reduction in study time is due to improved efficiency rather than cheating behaviors, it is crucial to independently demonstrate the increase in cheating behavior when assessing the impact of accountability partnerships. Therefore, we further report the effects of having a deskmate on pretending behavior. This differentiation is important because it helps ensure that the observed reduced learning time is, at least partially (35% revealed by an unreported mediation analysis), due to superficial learning (cheating) rather than improved efficiency. We calculate pretending behavior based on spending extremely little time memorizing words (essentially indicating word skipping). Due to the classification method, we condition the regressions on observations with memorizing at least one word. Results of OLS, Probit, and Logit models are reported in Table 4. All coefficients are positive and significant, indicating an increased chance of cheating. According to Column (1), a user in a deskmate relationship is 0.7% more likely to cheat, supporting our H1(c) that accountability partners increase cheating behaviors on OLPs.

Table 4. Deskmate's Effect on PretendingStudy

DV:	$PretendingStudy_{it}$		
	(1) Linear Probit (OLS)	(2) Probit	(3) Logit
$WithDeskmate_{it}$	0.007***	0.261***	0.516***
	(0.001)	(0.041)	(0.091)
User FE	Y	Y	Y
Date FE	Y	Y	Y
No. Observations	11,255,175	11,255,175	11,255,175
R2 / Pseudo R2	0.559	0.365	0.370
Notes: Robust standard errors are clustered at the user level. *p < .1; **p < .05; ***p < .01			

4.3. Heterogeneous Effects

4.3.1. Communication

Our H2 argues that communications between users would enhance the benefit of having an accountability partner and alleviate the harm. We leverage two features on Shanbay to measure communications between users in deskmate relationships. First, users can connect their WeChat with their Shanbay account to make communication easier. Connected users can receive reminders and encouragement from their deskmates on WeChat. Second, Shanbay used to allow users in deskmate relationships to direct message each other with any content. However, due to government regulations, the direct message function was canceled

on 08/18/2021. After that, users can only send each other emojis predefined by Shanbay, which significantly reduces communication. With the above two features, we construct two moderators: $WeChatReminder_{it}$ and $DirectMessage_{it}$. We estimate Equation (2) with the two moderators; results are reported in Table 5. Looking at the highlighted interaction terms, the positive coefficients in columns (1) and (2) indicate that more communication can boost both study probability and learning time. At the same time, results in column (3) show that communication could reduce the chance of cheating. Our H3 is supported.

Table 5. Moderating Effects of Communication

DV:	$CheckIn_{it}$	Log ($TotalStudyTime_{it}$)	$PretendingStudy_{it}$
	(1) Linear Probit (OLS)	(2) OLS	(3) Linear Probit (OLS)
Panel A: WeChat reminder as moderator			
$WithDeskmate_{it}$	0.419***	-0.035***	0.002***
	(0.002)	(0.009)	(0.000)
$WithDeskmate_{it}$ * WechatReminder	0.102*** (0.003)	0.021* (0.012)	-0.001*** (0.000)
Panel B: Availability of direct message as moderator			
$WithDeskmate_{it}$	0.324***	-0.080***	0.002***
	(0.000)	(0.001)	(0.000)
$WithDeskmate_{it}$ * DirectMessage	0.172*** (0.003)	0.127*** (0.001)	0.0001 (0.0001)
User FE	Y	Y	Y
Date FE	Y	Y	Y
No. Observations	62,816,619	27,893,348	19,384,734
Notes: Robust standard errors are clustered at the user level. *p < .1; **p < .05; ***p < .01			

4.3.2. Personal Goal

In H3, we argue that users with self-interest goals can stay intrinsically focused on the learning process without sacrificing outcome-motivated learning, thus enhancing the beneficial effects and alleviating the harmful effects of accountability partners. We measured goal orientation in the context of Shanbay as being "Not a student" and having an upcoming exam. Being "Not a student" represents a spontaneous goal orientation toward practical application or career advancement. Non-students are more motivated by practical career goals rather than academic ones. Having an upcoming exam represents a performance goal orientation. We estimate Equation (2) with the two moderators and report results in Table 6. The coefficients for interaction terms are highlighted. Based on Columns (1) and (2), we can observe that users with specific personal goals are more likely to check in, and their study time actually increased. Further, the two negative interactive terms in Column (3) reveal that users with specific goals would have a lower chance of pretending. These results provide evidence for our H4.

Table 6. Moderating Effects of Personal Goals

DV:	$CheckIn_{it}$	Log ($TotalStudyTime_{it}$)	$PretendingStudy_{it}$
	(1) Linear Probit (OLS)	(2) OLS	(3) Linear Probit (OLS)
Panel A: Whether is a student as moderator			
$WithDeskmate_{it}$	0.408***	-0.066***	0.002***
	(0.000)	(0.007)	(0.000)
$WithDeskmate_{it}$ * NonStudent	0.099*** (0.000)	0.117*** (0.014)	-0.002*** (0.000)
Panel B: Existence of exam force as moderator			
$WithDeskmate_{it}$	0.432***	-0.029***	0.002***
	(0.000)	(0.001)	(0.000)
$WithDeskmate_{it}$ * ExamForce	0.031*** (0.001)	0.043*** (0.003)	-0.001** (0.0002)
User FE	Y	Y	Y
Date FE	Y	Y	Y
No. Observations	62,816,619	27,893,348	19,384,734
Notes: Robust standard errors are clustered at the user level. *p < .1; **p < .05; ***p < .01			

4.4. Robustness Checks

We report a comprehensive set of robustness checks to support the validity of our main findings. An important assumption of a valid DID design is that relatively parallel trends existed (in providing answers) between the users with and without deskmate experience. We estimate relative time models to check this assumption. To visualize the long-term effects, we collapse the previous daily observations into monthly levels. Results are illustrated in Figure 2. First, most of the pre-deskmate coefficients are not statistically significant, suggesting that the two groups of users were comparable in learning behaviors before having deskmate. Second, we observe interesting dynamic effects. While the increase of study probability is stable in both long and short terms (Figure 2a), we observe that the decrease in learning time (Figure 2b) and increase in pretending (Figure 2c) only happen after more than one month into the deskmate relationship. For short-term relationships (within one month), having a deskmate actually marginally increases study time and decreases the chance of cheating. Considering 75% of deskmate relationships on Shanbay are within one month, the net value of the deskmate (accountability partner) feature for Shanbay would be positive.

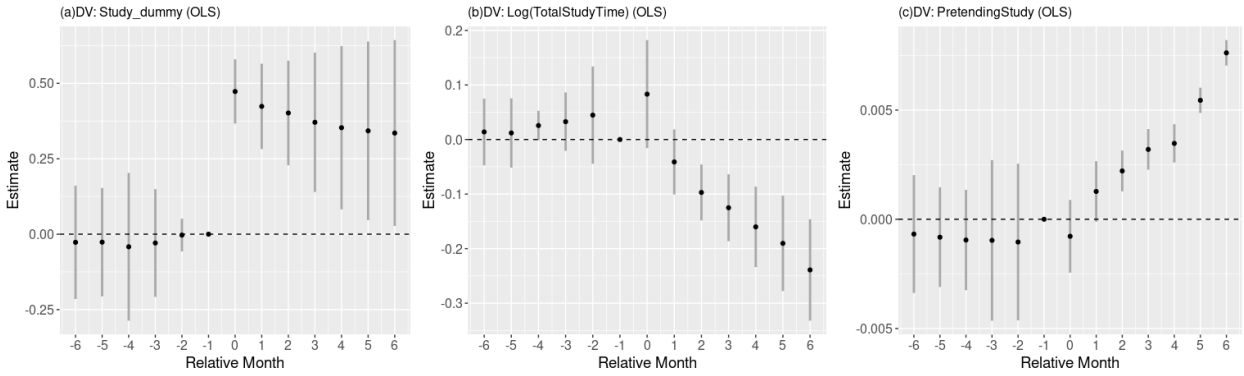


Figure 2. Results of Relative Time Models

In our main analysis, we leveraged all deskmate experience to estimate the effects of having accountability partners. We checked our results on two alternative samples to alleviate concerns due to self-selection issues and carryover effects. To avoid the potential influence of carryover effects (which are insignificant in an empirical check), we repeated our analysis on a sample that only contains control users and treated users' first deskmate experience. To address the concerns about self-selection biases, we construct a sample where only exogenous forced-out observations are included. Again, all results are consistent with our main analyses.

To overcome concerns about biases caused by time-variant unobservable, we adopted two alternative identification methods. First, we leverage the launch of the deskmate function on 02/01/2017 for a fuzzy regression discontinuity in time (Fuzzy RDiT) design and estimate the effects of accountability partners using 2SLS with the availability of the function as the instrumental variable. Results are reported in Table 7. They are qualitatively consistent with the main findings. Second, we apply the interactive fixed effects counterfactual (IFEct) estimator. Results are reported in Figure 3.

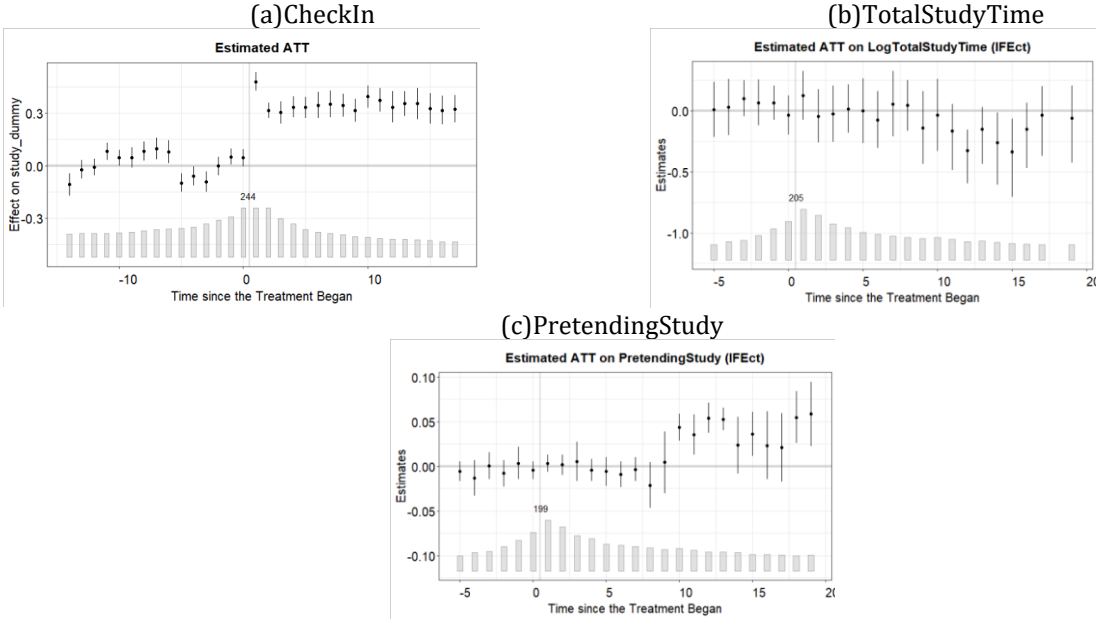


Figure 3. Results of IFEctm for (a) Check-ins, (b) Total Study Time, and (c) Pretending to Study

The directions and trends of estimated coefficients are consistent with the relative time models. The majority of pre-deskmate coefficients are insignificant. Having a deskmate stably increases a user's probability of checking in (Figure 3a). However, the harmful effects, i.e., reduced study time

(Figure 3b) and increased chance of pretending (Figure 3c), only appear in the long term.

Table 7. Results of 2SLS using the Launch of the DeskMate Function as the Instrumental Variable

DV:	$CheckIn_{it}$	Log ($TotalStudyTime_{it}$)	$PretendingStudy_{it}$
	(1) 2SLS	(2) 2SLS	(3) 2SLS
$WithDeskmate_{it}$	2.970***	-1.849***	0.034***
	(0.022)	(0.062)	(0.003)
First-stage F Stat	47,167.1	39,528.1	21,657.9
User FE	Y	Y	Y
No. Observations	1,661,316	1,041,034	637,394
R2	0.215	0.319	0.161
Notes: Robust standard errors are clustered at the user level. *p < .1; **p < .05; ***p < .01			

5. Discussions

The empirical findings contribute to the IS literature by exploring the impacts of accountability partners, an emerging social feature on OLPs. First, by documenting the phenomenon of pretending to study in online settings, we emphasize that OLP studies should pay attention beyond simple measurements of user engagements (e.g., check-in) but focus on users' actual learning. Second, our mechanism explorations on communication and personal goals provide valuable feedback for research on accountability mechanisms.

Moreover, the results offer practical guidance for OLP operators, suggesting that while accountability partnerships can boost engagement, careful consideration is needed to balance intrinsic and extrinsic motivations and to design features that minimize potential drawbacks. First, platforms should strengthen communications between partners to enhance social presence and provide a sense of monitoring. Second, to avoid the harmful effects of having an accountability partner, OLPs may consider shortening the duration of accountability partnerships or recommending users get new partners after a time threshold.

6. Conclusions and Limitations

Overall, this study finds that, on average, having an accountability partner on OLPs increases a user's likelihood of engaging with the platform. However, when studying does occur, users with accountability partners tend to spend less time studying. In this sense, the deskmate feature is a double-edged sword that boosts extrinsic motivation (easy-to-observe studying metrics) while reducing study time (hard-to-observe learning metrics). This dual nature is further reflected in the increased likelihood of users pretending to study, highlighting the risk of superficial learning behaviors driven by the desire to appear active rather than genuinely engage with the material. Notably, not all learners are affected in the same way. Our results show that learners with a high level of intrinsic motivation—those with personal goals—benefit more from such relationships. Our results indicate that goal setting not only increases platform check-ins but also alleviates negative consequences by promoting study time and reducing cheating behavior. Furthermore, our results provide practical implications for platform design, showing that increased communication among users reduces the negative effects of deskmate relationships (e.g., the frequency of fake check-ins), helping users stay connected. Over the long term, specifically when users have a deskmate for more than one month, the negative effects become more pronounced.

We also acknowledge several limitations of this study. First, while we applied several methods to alleviate potential concerns about identifying the causal impacts of having an accountability partner, there are still potential concerns due to the function's self-selection nature. Second, our analyses of archival data may not accurately capture some self-perceived constructs like personal goals. Therefore, we call for future research leveraging lab or field experiments to validate our findings further.

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