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Proactive student support using artificially intelligent conversational chatbots: The importance of targeting the technology

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Abstract

We examine through a field experiment whether outreach and support provided through an AI-enabled chatbot can reduce summer melt and improve first-year college enrollment at a four-year university and at a community college. At the four-year college, the chatbot increased overall success with navigating financial aid processes, such that student take up of educational loans increased by four percentage points. This financial aid effect was concentrated among would-be first-generation college goers, for whom loan acceptances increased by eight percentage points. In addition, the outreach increased first-generation students' success with course registration and fall semester enrollment each by three percentage points. For the community college, where the randomized experiment could not be robustly implemented due to limited cell phone number information, we present a qualitative analysis of organizational readiness for chatbot implementation. Together, our findings suggest that proactive outreach to students is likely to be most successful when targeted to those who may be struggling (for example, in keeping up with required administrative tasks). Yet, such targeting requires university systems to have ready access to and ability to make use of their administrative data.

Keywords: summer melt, artificial intelligence, chatbot, college access, student support

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Proactive student support using artificially intelligent conversational chatbots: The importance of targeting the technology

1. Introduction

Every spring, approximately 2.5 million US high school seniors are admitted to college. By September, approximately fourteen percent of those - 350,000 students - who intend to enroll succumb to “summer melt” and fail to matriculate (Castleman & Page, 2014a, 2014b; Castleman, Page, & Schooley, 2014). Students who “melt” over the summer disproportionately come from underserved communities that frequently lack the supportive resources to help students navigate challenging financial, academic, and social situations.

Nudging college-intending students by sending them text messages with information and reminders has been an effective strategy for reducing summer melt (Castleman & Page, 2015; Castleman et al., 2014; Page & Scott-Clayton, 2016). When students receive timely and tailored information about which steps to undertake for college enrollment along with reminders about how and when to complete these enrollment-related actions, they are more likely to successfully matriculate on time (Castleman & Page, 2015, 2016; Castleman et al., 2014; Page, Castleman, & Meyer, 2016; Page, Kehoe, Castleman, & Sahadewo, 2019).

Artificial intelligence (AI) enabled chatbots use the recent advancements in machine learning to provide tailored and timely support college-intending students and therefore hold much potential for scaling student outreach and support effectively and at a low cost. Page and Gehlbach (2017) demonstrated that artificially intelligent chatbots can be an effective tool to reduce summer melt. Specifically, the authors experimentally tested the effect of an AI-enabled chatbot designed by AdmitHub for Georgia State University (GSU) and found that chatbot outreach increased GSU-intending students’ success with a variety of pre-matriculation tasks and on-time enrollment.

These results parallel prior research on summer melt (Castleman, Owen, & Page, 2015; Castleman & Page, 2015; Castleman et al., 2014). However, because the AI can manage the majority of student communication without ongoing staff input, it allows college admissions and financial aid staff to redeploy their time on issues that only experienced counselors can solve, making the chatbot intervention highly promising for scaling up.

This study addresses three questions that arise from the Page and Gehlbach (2017) findings. First, can the impacts from that study replicate to other settings? Page and Gehlbach (2017) explore only one context (Georgia State University), and our study helps us understand whether the positive effects observed generalize to other settings. Second, are there students for whom the outreach is particularly beneficial? Results from the GSU study yielded suggestive evidence of differential effects by student characteristics. And third, from an implementation standpoint, what conditions need to be in place for a college or university system to successfully implement a centralized communication tool such as a chatbot? Lessons learned from implementation challenges that we study in one of our two focal settings help to explore this question.

To answer these questions, in partnership with East Carolina University (ECU) and Lenoir Community College (LCC), we tested the capacity of AI-enabled chatbots to improve students' success with completing required pre-matriculation tasks and enrolling in college in the fall of 2018. Each institution had a campus-specific chatbot named for their respective mascots. "PeeDee," was tailored to the ECU context, and the other, "Lance," was an analogous system designed for LCC. In both settings, the chatbot communicated with students via text messages to provide them with reminders and follow up support regarding the logistical and administrative tasks that students must complete to successfully matriculate to college.

To preview our findings, in contrast to the GSU context, we observed that the rate of summer melt was relatively low for students overall. Nevertheless, the text-based outreach did increase students' success with navigating the financial aid process and gaining access to student loans by four percentage points. Further, the outreach improved several outcomes for a critical subgroup of students at ECU, namely, those who are first in their family to attend college. For these students, the outreach increased the probability of accepting a loan by eight percentage points, the probability of registering for classes by three percentage points, and the probability of enrolling at ECU by three percentage points. The findings at ECU indicate the importance of targeting the chatbot interventions to categories of students who may be struggling (for example, in keeping up with required administrative tasks) and, therefore, prone to summer melt.

Turning to LCC, we learned quickly that the college lacked cell phone information for a substantial share of students who were otherwise eligible for outreach at the beginning of the summer of 2018, and this hindered initial project implementation as well as the associated experimental study. Given the limited nature of the LCC implementation, we instead turned our focus at LCC to lessons regarding chatbot implementation readiness. We conducted in-depth, semi-structured interviews with the LCC staff involved with chatbot implementation and found that, in addition to technical requirements such as valid cell phone number information for students, the implementation of a centralized communication tool such as the one we explore required considerable learning and adaptation from both the college staff and the chatbot developers. At the same time, LCC was able to overcome these implementation challenges, and staff report that the use of the chatbot helped LCC to reach and engage students more proactively, although we do not have experimental evidence to support this claim. Further, staff report that the implementation process served as a driver of organizational learning, as it helped the staff to better understand and articulate their admissions and enrollment processes. Taken together, our findings suggest that in considering those use of a tool such as this, campuses should consider both the potential to improve outcomes for their students as well as their institutional readiness and capacity for implementation.

We structure the remainder of the paper as follows: section 2 reviews the relevant literature and provides background and context for the study, section 3 presents the details and results of the randomized controlled trial at ECU, section 4 reports on the qualitative analysis of the chatbot implementation readiness at LCC, and section 5 discusses the findings and concludes.

2. Background and context

Summer melt is the phenomenon whereby college-intending high school graduates "melt away" during the summer and fail to matriculate to college in the fall semester due to challenges in navigating required pre-enrollment tasks and processes (Castleman & Page, 2014a, 2014b). Lack of family support, financial resources, and knowledge of the higher education system are key correlates of college-intending high school graduates faltering in realizing their college-going plans (Arnold, Fleming, DeAnda, Castleman, & Wartman, 2009). For students succumbing to summer melt, it is challenging to complete all necessary enrollment-related steps, including evaluating financial aid offers, meeting unanticipated costs, filing paperwork, making housing arrangements, taking placement tests, etc. Summer melt affects an estimated 10% to 20% of college-intending students each year, with higher rates among low-income and first-generation college students (Castleman & Page, 2014b).

Several studies have examined whether proactively communicating with and supporting college-intending students via text messages may reduce summer melt. Text messaging campaigns leverage behavioral economics research on how nudges, or timely prompts, increase completion of tasks that benefit both the individual and the society, such as getting flu vaccines or saving money for retirement (Thaler, 2016; Thaler & Sunstein, 2008; Tomer, 2017).

Multiple studies confirmed that nudging students helps to effectively reduce summer melt and improve completion of college-related administrative tasks. For example, in a randomized controlled trial in four urban school districts, Castleman and Page (2015) showed that personalized text messages reminding high school students of enrollment-related steps increase college enrollment among students with limited access to college counseling support and information. Through a randomized controlled trial in eight school districts in Texas, Page et al. (2016) demonstrated that nudges reminding students of the status of their application for federal financial aid (FAFSA) and offering helpful and relevant resources increasing financial aid application submission and timely college enrollment. Overall, studies of the effect of nudging on summer melt indicate that nudges reduce summer melt through giving students access to information about completing enrollment-related tasks and by directing students towards additional help if needed (Castleman & Page, 2013; Castleman et al., 2014; Castleman, Schwartz, & Baum, 2015; Page & Nurshatayeva, 2020).

Although early studies have found nudge-type outreach to be successful in improving students' timely transition to college, recent efforts to scale such interventions at the national level of proven less promising. This may be because broadly implemented interventions have smoothed over contextual variation in students' needs to such an extent that the outreach is no longer meaningful or salient for them. As Bird and colleagues (2019) suggest, this may point to the comparative advantage of scaling through concerted implementation across contexts but at the local level such that students are able to receive relevant information from a trusted source.

In recent years, advances in computer science have enabled the development of artificially intelligent (AI) chatbots, which offer new opportunities to provide summer melt preventive text messaging support to college-intending high school graduates. In addition to providing information and reminders about completing enrollment-related steps, chatbots offer students an opportunity to interact by asking questions and receiving real-time responses drawn from a knowledge base. In cases where the AI cannot answer a student's question, the communication system is designed to transmit the question to a designated campus staff member. The system is able to learn over time and become more efficient in responding to questions and requests. The AI-enabled interactivity, automatic and timely tailoring of text-messages to each students' needs, and the potential for scalability make conversational chatbots an attractive student support technology that may improve college access and success.

We follow Page and Gehlbach (2017), who studied the effect of AI-enabled chatbots on summer melt at Georgia State University. Specifically, in this study we sought to examine the effect of student outreach and support via AI-enabled chatbots on student completion of pre-matriculation tasks and timely enrollment at two higher education institutions, East Carolina University (ECU) and Lenoir Community College (LCC). During the study implementation process, we quickly learned that logistical challenges would hinder the implementation of the experiment at LCC. Therefore, at LCC, we turned to a qualitative exploration to inform our understanding of factors that support and impede successful chatbot implementation.

3. The randomized controlled trial at East Carolina University

3.1 Setting: East Carolina University (ECU)

East Carolina University is a public, four-year research university located in Greenville, North Carolina. Every year, ECU enrolls a freshman class of approximately 4,400 students.

Among undergraduate students, approximately 84% are in-state, and 34% receive Pell grants (National Center for Education Statistics, 2018). ECU has a mission to serve the rural eastern North Carolina and currently serves more students from the state's lower-income counties than most colleges in the University of North Carolina System.

3.2 Randomization procedure at ECU

For the study, ECU first identified students who qualified for outreach. These were students whom the university classified as intending to enroll at ECU in Fall 2018. A total of 4,442 prospective ECU students participated in the study. We randomly assigned 2,221 students to the treatment group and 2,221 students to the control group. Students assigned to the active treatment condition were targeted for chatbot outreach in addition to all other business-as-usual ECU communication. Students assigned to the control condition received business-as-usual communication but did not receive outreach from the chatbot during the intervention period.

As illustrated in Table 1, the average baseline characteristics of the ECU treatment and control groups are statistically indistinguishable, i.e. randomization worked. Participating students are about 18 years old, on average. Female students comprise slightly more than half of the sample. Among participating students, 66% are white, 15% are Black, 8% are Hispanic, 3% are Asian, 1% are Native American, and about 6% are multiracial. About 19% of the participants are first-generation students, and approximately 87% are in-state students. The average study participate has a math-verbal combined SAT score of 1,106, roughly the 58th percentile of the national distribution.

3.3 Intervention at ECU: PeeDee

In collaboration with AdmitHub, ECU introduced an AI chatbot (named PeeDee for the university's mascot) into the university's enrollment process for prospective students assigned to the treatment group. The chatbot was designed to: nudge students with reminders relevant to their individual required enrollment and matriculation processes and provide them with timely answers to their questions.

University staff designed primary outreach messages, also referred to as text messaging “campaigns”, focusing on:

1. Introduction to the chatbot: introducing students to PeeDee’s functionality and offering an opportunity to opt out of using PeeDee’s assistance
2. Orientation: reminding students to register for orientation and providing the details such as dates and registration links
3. Class registration: reminding students to register for courses and asking whether any information or help was needed
4. Housing: reminding and providing information about actions necessary for timely moving into residence halls
5. Social involvement: invitations to join the campus’s official social media groups and to participate in events targeted for freshmen
6. Academic exploration and general enrollment: providing information and offering assistance with degree programs, etc.
7. Rapport building: less-serious messages, such as fun facts about the campus, ECU trivia, and congratulations on the first day of classes.

The university employed the chatbot to text intending ECU students assigned to the treatment group throughout the summer of 2018. Text messaging campaigns sent out to students were either nudges containing reminders to complete matriculation-related actions or interactive messages that invited students to respond to the chatbot. As noted, students were offered the opportunity to opt out at the beginning of the intervention and could opt out (via text) at any time during the course of the outreach. Where possible, text messaging campaigns were tailored to students' specific needs, based on administrative records held by the university. For example, if students had already submitted required paperwork to verify their in-state residency, they did not receive outreach about doing so.

Table 2provides descriptive information on the timing and distribution of the ECU chatbot messaging campaigns. We report on the main categories of student-bound messages but not the contents of additional messages that resulted from the students' interaction with the chatbot. The intervention ran from the beginning of July to nearly the end of August. Throughout the summer, the share of treatment students to receive the outreach varied according to message intention and need. For example, nearly all treatment group students received the introductory message, but only about 10% of students received a reminder to use ECU's internal system to register for courses. The remaining 90% had likely already registered for courses and therefore did not need the message. Such variation is indicative of how the chatbot tailored the outreach to each student's needs.

3.4 Data and analysis at ECU

We rely on ECU's administrative data to examine impacts of the outreach on completion of required pre-matriculation tasks (e.g., attending orientation or registering for courses). In addition, we used ECU's administrative data linked to records from the National Student Clearinghouse (NSC) to examine whether students who did not enroll in ECU opted to enroll elsewhere.

For all outcomes, we estimated treatment effects using a linear probability model, as follows:

$$Y_i = \alpha + \beta_1 TREATMENT_i + \boldsymbol{X}\gamma + \epsilon_i \tag{1}$$

where $TREATMENT_i$ is an indicator for assignment to the treatment group, $\boldsymbol{X}$ is a vector of student-level covariates included to improve the precision of our treatment impact estimates; and ϵ_i is a residual error term. Our estimates of the β_1 coefficient indicate whether targeting students for outreach served to improve student success on the outcome measures considered. Specifically, we test whether students from the treatment group are more likely to complete the following matriculation-related outcomes: (1) enroll at ECU in the fall of 2018, (2) accept a loan, (3) attend orientation, (4) register for classes, (5) register for a greater number of course credits, (6) register for more courses, and (7) enroll at any four-year college.

3.5 ECU-intending students' interactions with the AI chatbot

In Table 3, we present descriptive statistics on the interactions between ECU-intending students and PeeDee for the sample overall as well as separately by first-generation status. Approximately six percent of the students in the entire treatment group opted out PeeDee outreach during the course of the intervention (Table 3, column 1). Such low level of opt-out is in line with other implementations of text-based summer outreach (Castleman & Page, 2014a). The typical treatment group student received approximately 26 messages from PeeDee throughout the summer (including both the targeted campaigns and the chatbot's responses to students' queries). The messages were tailored to considerably wide-ranging needs and varied by students' responsiveness to the system, so some students received as few as three messages while other students received as many as 97.

In response to PeeDee's outreach, the typical treatment group student sent three messages, on average. Some students did not send any messages, whereas others interacted more frequently. The most engaged student sent PeeDee 52 messages during the course of the summer intervention.

The details on the number of days on which students sent messages tell a similar story of engagement heterogeneity. Specifically, some students never sent any messages while other students interacted with the chatbot on many more days, up to 22 days at most. These numbers suggest that some but not necessarily all students have a variety of needs during the summer before starting college. These descriptive statistics suggest that the chatbot is a useful tool for proactively prompting questions and then handling this variation in needs.

The remainder of Table 3 presents summary statistics on the interactions with the chatbot of first-generation students (columns 3 and 4) compared to non-first-generation students (columns 5 and 6). The level of opt-out and average engagement were similar for first-generation and non-first-generation students. However, the maximum values of the engagement metrics differ according to first-generation status. For example, the maximum number of text messages sent by the chatbot to first-generation students (97) was much higher compared to the non-first-generation students (69). The maximum number of messages sent to PeeDee was higher among first-generation students (52) compared to non-first-generation students (34). The maximum number of days (22) interaction with PeeDee occurred was also among the first-generation group. Collectively, these estimates suggest that the average system engagement was similar by first-generation status even though the most active users of the chatbot support were among first-generation college-goers.

3.6 Treatment effects at ECU

In Table 4, panel A, we present treatment effect estimates for the full sample. Of the outcomes we consider, the chatbot outreach improved only one outcome: whether ECU-intending students accepted a loan. Specifically, students in the treatment group were approximately four percentage points more likely to accept a loan as a result of being targeted for outreach (column

2). At the same time, the outreach had no effect overall on course registration, orientation attendance or ECU enrollment. Note that the control group means suggest that baseline values of each outcome variable, except for loan acceptance, were quite high. In other words, there was little room for improvement in terms of outcomes of interest for the full sample.

By contrast, for first-generation students assigned to the control condition, rates of success with pre-matriculation tasks and timely enrollment are lower than for the sample overall, so first-generation students had comparatively more room for improvement on these outcomes. Treatment effect estimates for these students (Table 4, panel B) indicate positive effects of the chatbot outreach. Specifically, first-generation students in the treatment group were nearly eight percentage points more likely to accept a loan, three percentage points more likely to enroll at ECU, and three percentage points more likely to register for classes compared to the first-generation students in the control group. Further, our estimates using subsamples of data by first-generation student status suggest that the effect of the treatment on loan acceptance in the pooled sample is predominantly driven by the effects on the first-generation students. That more positive effects were concentrated in the subsample of first-generation students at ECU is consistent with the overall prevalence of summer melt among the less advantaged youth.

3.6 Comparison of results to the chatbot effects at Georgia State University

We considered possible explanations for the limited treatment effects except for the loan acceptance outcome in the pooled ECU sample. First, we explored whether the AI chatbot service was relevant for the ECU students. As the control group means in Table 4 illustrate, 93% of the students had enrolled and 89% registered for classes without outreach or support from the chatbot. Further, the control group students, on average, registered for practically a full-time semester course load of about 5.4 courses or approximately 14 course credits for fall 2018. These control group figures suggest that, for the sample as a whole, there was little room left to improve upon most of the outcomes examined in this study. For colleges and universities considering use of a tool such as this, these control group rates point to the importance of a needs analysis to understand whether or the extent to which implementation is meeting challenges that are being faced in a particular context.

The analysis of the messages the students received reveals that students completed most of the enrollment-related steps prior to the treatment implementation. For example, only 158 students (7% of treatment group) received a message related to course registration. In other words, some of the chatbot messages were focused on actions that many ECU-intending students completed on time. Loan acceptance, in contrast, was completed by most students during the summer, as shown in Figure 2. Such temporal concentration of the loan-related tasks may help to explain why we find positive treatment effects on loan acceptance.

Further, we compared the ECU student body characteristics to the characteristics of students at Georgia State University (GSU) where chatbot outreach improved several outcomes for GSU-intending students overall (Page & Gehlbach, 2017). A detailed comparison of ECU and GSU indicates that the differences in the two institutions' student bodies possibly explain the differences in the chatbot effects. As Table 5 reveals, the student bodies at the two campuses are substantially different. For example, the share of first-generation college students is about 18% at ECU, compared to 32% at GSU. As we might expect, the rate of summer melt at GSU was also substantially higher. In sum, ECU students tend to be more advantaged socioeconomically and less prone to summer melt than the GSU students.

4. Chatbot implementation readiness: Lessons learned at Lenoir Community College

We were unable to implement our initial plan to estimate the effect of chatbot outreach on summer melt at Lenoir Community College because upon receipt of data for randomization, we learned that the college had cell phone contact information for only a small fraction of potentially incoming students. To inform future efforts to use text-based communication such as the type we describe in this paper, at LCC we turned to a qualitative examination of factors that may hinder or support chatbot implementation in a community college context. To note is that even though LCC was unable to launch the chatbot in a manner conducive to an experimental study, over a longer time horizon, they did work with and launch the tool in a manner that campus staff considered highly fruitful. We explore the campus's progression to implementation here.

4.1 Setting: Lenoir Community College (LCC)

Lenoir Community College is a public, two-year open-admission community college located in Kinston, North Carolina. LCC's student population comprises about 2,700 undergraduate students enrolled in associate's degree programs or certificate programs offered both in-person and online. About 61% of the full-time undergraduate students at LCC receive Pell grants (National Center for Education Statistics, 2018). LCC's mission is to provide accessible higher education for the development of the students and the community.

4.2 Data collection and analysis at LCC

We conduct three semi-structured interviews, each lasting between 30 and 60 minutes, with staff members directly involved with implementing the AI chatbot at LCC. To address potential "built-in blind spots" and collect better data, we followed Miles, Huberman, and Saldaña (2014) and started analysis concurrently with the data collection. After audio-recording and transcribing the interviews into text, two researchers independently coded the data to derive patterns and general themes through jotting and analytic memoing (Saldana, 2013). Coders were in agreement 100% of the time.

4.2 Lessons learned from chatbot implementation at LCC

The analysis of the interview data collected at LCC highlighted the following themes regarding implementation.

Adapting the chatbot for the community college context

LCC was the first community college to implement the AdmitHub chatbot to address summer melt. In the process of implementing the chatbot, it became clear that the design of the chatbot was comparatively better suited to the four-year college context. For a small-scale community college like LCC, where the student body is very fluid and changeable, the chatbot could not be utilized as straightforwardly as in a typical four-year college. As one LCC staff member explained:

> One of the disadvantages that we have is that unlike a university that probably has some hard deadlines for admissions and registration, we're really fluid here. It's possible that somebody is going to apply for this current semester on December 2nd and register for a class that starts December 2nd. I can tell you who our currently enrolled students are today, but that could very well change tomorrow, because we could register somebody tomorrow for a class that's going to start very soon.

Both the LCC staff and AdmitHub developers had to invest considerable time and effort for the chatbot to function as intended. LCC staff had to figure out how to utilize the chatbot in their context. Specifically, they had to prepare information for the chatbot's knowledge base, learn the admin interface for operating chatbot's functionality, study what the chatbot is capable of doing in their specific context, etc. At the same time, the chatbot developers had to learn about the community college context in order to assist LCC staff who administered the chatbot implementation.

Another example of how the fluid nature of a community college operations required the chatbot to be used differently is related to tuition payment deadlines. Typically, four-year colleges have a single, institution-wide tuition payment deadline each term. In contrast, in the community college context, different deadlines are relevant for different students, as explained in the following:

> I've had to send one [campaign] to remind students that tuition was due, and our tuition is due five days before the class starts, but we have classes that start on the first day of the semester, we have classes that start two weeks later, and we have some classes that are getting ready to start October 15th, we even have classes that start December 2.

Because of this more variable course-start time structure, sending a text message to remind students about a seemingly straightforward detail as the tuition payment deadline involves multiple, different outreach campaigns distributed at different times. As a result, implementation of the chatbot within the LCC context required far more manual customization of the messaging campaigns so that students received the messages that were appropriate in terms of timing and content.

Implied by the variation in course start time is the fact that LCC also had a more fluid and ongoing admissions process which required that the chatbot be used far beyond the summer. Therefore, the summer melt campaigns had to be reframed and redeployed for a system of more constant communication with students. The chatbot implementation experience at LCC suggests that the concept of summer melt should likely be redefined in the community college context as an "on-going pre-enrollment melt" to capture how students intending to attend a two-year college might fail to enroll at any time of the year and not only during the summer. Melt prevention appears to be necessary beyond the summer in community colleges.

Limited functionality due to a lack of chatbot's integration with LCC databases

A strength of the chatbot tool is the ability to integrate it with an institutional student information system to use administrative records to inform the targeting of outreach. For example, a message about FAFSA refiling can be sent only to those students who haven't refiled by a particular deadline. At LCC, however, this integration was not initially possible.

Therefore, in the LCC context, sending tailored messages to students required more manual work, as one staff member described:

> The communication developed in campaigns was not necessarily dynamically reaching the students who needed it. We had to run queries to identify students, and so the lack of data integration between the bot and our enrollment system is the major challenge. If I had to send a message to 400 students, but really 100 of those students have already resolved what I needed them to resolve or that message is not relevant for them any longer … if the chatbot could extract that information and develop a campaign based on that, that would be the type of dynamic communication that would really take advantage of the chatbot.

Instead, to implement a targeted outreach campaign, LCC staff had to manually query the college's database and import the list of relevant students into the chatbot platform to then send a targeted text campaign. For example, after an initial text message inviting students to the orientation event, an LCC staff member would have to obtain from the institutional data analyst a list of those students who had not yet registered for orientation and enter that list into the chatbot system. Then it was possible to send a reminder text message about the orientation event to these students. The staff member would have to repeat this process for each follow up message focused on orientation. Otherwise stated, LCC was not able to employ the tool's automatic text message tailoring functionality due to a lack of system integration. Thus, chatbot implementation was labor-intensive for LCC staff. Rough estimates suggest that an LCC staff member could spend three to five hours sending a single text messaging campaign, from preparing lists of students to sending the intended text message.

This lack of automation occurred because a robust link between the chatbot system and LCC's database system could not be established. Therefore, campuses considering the implementation of this type of tool should involve their technology and data teams to ensure system integration.

Chatbot as a communication tool and a driver of institutional learning

Even though LCC initially faced several challenges to robust and efficient implementation, after working through these challenges, LCC found the chatbot very useful and chose to continue to use the tool beyond the timeframe of the grant-supported implementation. In short, it took a longer timeframe (approximately six months) for LCC to adapt the tool and integrate it to its campus context. By the second year of implementation, LCC staff confidence in using the chatbot tool was substantially higher, as one staff member describes:

> … I think probably six months into the process we really started to understand the idea of the chatbot. We started to see the benefits of the chatbot. The second year has been very good for us. We've been able to use it in very creative ways and very strategically, as well as tactically when contacting students. … once we were able to understand the concept of the chatbot, then the creativity of an admissions director, a registrar, financial aid director, we could really take advantage of their ideas.

That is, after the initial period of adaptation and learning, LCC staff were able to harness the opportunities offered by the immediacy and interactivity of chatbot's text messaging functionality.

LCC staff expressed appreciation for the speed with which the chatbot enabled them to reach out to and interact with large numbers of students. As a member of LCC staff put it:

> What we really learned is that students respond much more effectively or efficiently when we have direct communication with them via text [messages] and when they can respond and ask their question through that thing [the chatbot]. We tried postcards, we tried email, we tried other sources of communication, and what we found is that with the chatbot we could really engage students very quickly and get them to respond through those requests very quickly.

In other words, the mode of communication through text messages and the interactivity of the chatbot enabled LCC to connect and engage with the students more effectively compared to other modes previously employed. This improved communication translated to faster resolution to issues students faced. For example, LCC typically observed that about 10% of associate's degree students would not have paid their tuition in the days prior to the start of a semester. After sending a series of text messages focused on bill payment through the chatbot, LCC staff observed that the text outreach speeded up student activity in terms of calling the campus cashier's office, traveling to the office to pay in person, and paying one's tuition bill online. While by design the chatbot was "learning" and getting better at responding to students' questions, engaging in the chatbot implementation process also sparked new learning among LCC staff themselves. For example, LCC staff consolidated a comprehensive knowledge base from which the chatbot could draw and learned how to update it. Further, they established more regular communication channels among the admissions, registrar, institutional research office, and the staff members administering the chatbot campaigns. The LCC team also reported getting better over time at planning and targeting their chatbot campaigns. For example, they reported gaining proficiency in crafting text message content so that the language is clear but brief enough to fit the character limitation of a text message. Finally, the process pushed staff to attend more carefully to alignment in information via various channels of communication (e.g., whether information on the college website aligned with information they were communicating to students via text). In sum, although data and process barriers hindered quick ramp up to implementation in the context of an experimental study, LCC successfully integrated the chatbot tool into their student communication strategy over a longer time horizon that allowed for institutional learning and necessary adaptation.

5. Discussion and conclusions

At ECU, we observe evidence in alignment with that from other campuses (e.g., Georgia State University; Page & Gehlbach, 2017) as well as the broader research literature on summer melt (Castleman, Owen, et al., 2015; Castleman & Page, 2015; Castleman et al., 2014). That is, when systems are in place to robustly launch chatbot communication focused on summer transition tasks, it can lead to improvement in student success with pre-matriculation requirements as well as with successful matriculation. In the context of ECU, positive impacts of the chatbot tool were realized primarily by students who would be the first in their family to attend college. For these students, the outreach improved students' success with accessing financial aid for college, matriculating on time, and registering for courses. That impacts are realized primarily by this subset of students is not surprising, as they may experience less household knowledge about college-going processes compared to their non-first generation peers, and the baseline rates of success with various college-going processes were lower for the first-generation students in our sample.

Consistent with existing literature, students who "melt" over the summer disproportionately come from underserved communities that frequently lack the supportive resources to help students navigate challenging financial, academic, and social situations related to college matriculation (Castleman & Page, 2015). Our analyses comparing the findings at ECU to the effects of chatbot support identified earlier at Georgia State University show that, on average, ECU students tend to be more advantaged socioeconomically than students who attend GSU and, as a result, may be less susceptible to summer challenges that can lead to melt. That more positive effects were concentrated in the subsample of first-generation students at ECU is also consistent with the overall prevalence of summer melt among the less advantaged youth. The findings at ECU highlight the importance of targeting the chatbot assistance to the students who are more prone to succumb to summer melt. Universities contemplating the use of chatbots should begin by identifying the target categories of students who will likely benefit from the outreach and support.

Chatbot tools such as those investigated here are typically framed as relatively low-cost, however, our study shows that this framing relates only to the technology itself. As our learnings from LCC reveal, successful implementation and ongoing tool usage can necessitate the input, collaboration, and communication among various staff members and offices on campus. If these entities are more accustomed to working in a siloed fashion, successful implementation of a centralized communication tool, such as a student-facing chatbot, can require substantially different business routines. These disparate entities will need to communicate and coordinate more regularly, and new systems of data access and sharing may also be required. Our findings from LCC indicate that in contexts where staff are able to dedicate time and effort to this type of required system-level change, it is possible to successfully implement a new communication strategy, such as a chatbot. However, as we observed in the LCC context, the potential efficiencies that a chatbot tool can offer may take longer to realize, as the tool is adapted to the particular context and the organization systems and procedures are adapted to support implementation. Because higher education institutions differ considerably in size and scale of operation, the successful design and implementation of chatbots should likely begin with identifying pre-enrollment melt patterns throughout the academic year using a given institution's administrative data.

In sum, the findings across these two sites help to bolster the evidence that an artificially intelligent chatbot tool has the potential to improve college access in a variety of contexts. We contribute to the growing body of literature examining the potential of technology-supported behavioral interventions in education to scale up (Bird et al., 2019; Gurantz et al., 2020; Page & Nurshatayeva, 2020; Page, Sacerdote, Goldrick-Rab, & Castleman, 2019). Our findings are aligned with the notion that behavioral interventions using artificially intelligent chatbots cannot be centralized at a massive scale, and instead, should be carefully implemented institution-by-institution. The lessons learned from LCC serve to highlight the data and communication systems and routines that need to be firmly in place in order to support successful implementation. These learnings may inform the types of feasibility assessments in which institutions ought to engage to understand the institutional resources and commitment that are required for a tool such as this to be incorporated fruitfully into regular student communications. At the same time, even though it took LCC time to change their practices, as they did so, they came to see how the chatbot was useful in their working with students in a more student-centered way.

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Tables and figures

Table 1. Demographic characteristics of ECU participant students

	(1) Pooled sample		(2) Treatment group		(3) Control group	
	mean	(sd)	mean	(sd)	mean	(sd)
Age	17.95	(0.50)	17.94	(0.48)	17.96	(0.52)
Female	0.58	(0.49)	0.59	(0.49)	0.57	(0.49)
White	0.66	(0.47)	0.65	(0.48)	0.67	(0.47)
Black	0.15	(0.35)	0.15	(0.36)	0.14	(0.35)
Hispanic	0.08	(0.27)	0.08	(0.27)	0.08	(0.27)
Asian	0.03	(0.16)	0.03	(0.16)	0.03	(0.17)
Native American	0.01	(0.08)	0.00	(0.06)	0.01	(0.09)
Multiracial	0.06	(0.23)	0.07	(0.25)	0.05	(0.22)
First-generation student	0.18	(0.38)	0.17	(0.38)	0.19	(0.39)
In-state	0.87	(0.33)	0.87	(0.34)	0.88	(0.33)
SAT	1,105.89	(120.22)	1,108.14	(119.63)	1,103.63	(120.79)
Observations	4,442		2,221		2,221	

Note. None of the differences between the treatment and control groups are statistically significant.

Table 2. Overview of the chatbot text messaging campaigns at ECU (07/02/2018-08/24/2018)

Chatbot messages to students	Date	% of treatment group recipients
1. Introductory message and offer to opt-out	07/02	99
2. Reminder to register for orientation	07/02	99
3. Happy 4th of July message	07/04	96
4. Reminder to use the internal registration support system	07/05	10
5. Reminder & link to info about how to prepare for moving into residence halls	07/09	84
6. Invite to join the Facebook group of class 2022 with a link	07/13	95
7. Reminder to explore degree programs	07/18	95
8. Reminder to check the admitted students guide	07/20	95
9. College fun facts trivia	07/24	95
10. Reminder to complete NC residency determination for out-of-state students	07/26	1
11. Reminder about the move in day	07/31	84
12. Ask students if they need help registering for classes	08/11	7
13. Reminder to register for classes	08/14	6
14. Song trivia	08/16	95
15. Invitation to the fun event for freshmen	08/17	94
16. Wishing good luck on the first day	08/20	94
17. Reminder about the last day of add/drop	08/24	93
18. Survey on what students think about the chatbot	Variable	84

Table 3. Statistics on the interactions between PeeDee and the treatment ECU-intending students

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled sample		First-generation students		Non-first-generation students	
	mean (sd)	range	mean (sd)	range	mean (sd)	range
Opt out	0.06 (0.23)	0-1	0.05 (0.21)	0-1	0.06 (0.24)	0-1
Messages sent by PeeDee to students	26.37 (7.51)	3-97	26.52 (7.68)	3-97	26.32 (7.45)	3-69
Messages sent by students to PeeDee	3.36 (4.53)	0-52	3.24 (4.98)	0-52	3.40 (4.37)	0-34
Number of days during which students sent messages to PeeDee	1.42 (1.71)	0-22	1.38 (1.94)	0-22	1.43 (1.63)	0-13
Observations	2,205		548		1,659	

Table 4. Average treatment effects

	(1) Enrolled at ECU	(2) Accepted loan	(3) Attended orientation	(4) Registered for classes	(5) Number of credits registered for	(6) Number of courses registered for	(7) Enrolled at any four-year college
A. Full sample estimates							
Treatment	-0.007	0.036**	-0.005	-0.007	-0.108	-0.046	-0.005
	(0.008)	(0.015)	(0.008)	(0.008)	(0.125)	(0.053)	(0.006)
R-squared	0.02	0.05	0.01	0.02	0.01	0.02	0.01
Control group mean	0.93	0.55	0.92	0.93	13.81	5.44	0.96
	(0.01)	(0.01)	(0.01)	(0.01)	(0.09)	(0.04)	(0.00)
Observations	4,442						
B. First-generation sub-sample estimates							
Treatment	0.034*	0.078**	0.002	0.034*	0.378	0.100	0.025
	(0.020)	(0.032)	(0.019)	(0.020)	(0.315)	(0.132)	(0.017)
R-squared	0.01	0.06	0.03	0.01	0.02	0.02	0.02
Control group mean	0.89	0.63	0.92	0.89	13.18	5.18	0.92
	(0.01)	(0.02)	(0.01)	(0.01)	(0.24)	(0.10)	(0.01)
Observations	849						

*** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses. Results based on regression models that control for all covariates presented in Table 2.

Table 5. Comparing ECU and GSU characteristics

	(1) East Carolina University	(2) Georgia State University
	A. Data from IPEDS 2015	
% admitted	70	59
Admission yield	36	41
% receiving undergraduate degree within 4 years	34	23
% receiving undergraduate degree within 6 years	61	53
In-state tuition	$ 4,365	$ 6,846
Out-of-state tuition	$ 20,323	$ 21,414
	B. Data from College Scorecard	
Minority-serving	No	1. Asian-American & Native American Pacific Islander-serving institution 2. Predominantly black institution
Average annual net price for federal financial aid recipients	$ 15,203	$ 14,773
Median salary of federal financial aid recipients 10 years after attending	$ 40,500	$ 43,300
Students receiving federal loans	55%	56%
Students who return after their first year	81%	81%
Full-time students	88%	78%
Pell grant recipients	33%	51%
White	68%	25%
Black	16%	42%
Hispanic	6%	10%
Asian	3%	13%
SAT verbal 75th percentile	560	590
SAT math 75th percentile	570	590
Most popular programs	1. Health and related 19% 2. Business, management, marketing, and related 18% 3. Education 8%	1. Business, management, marketing, and related 25% 2. Social Sciences 10% 3. Psychology 9%

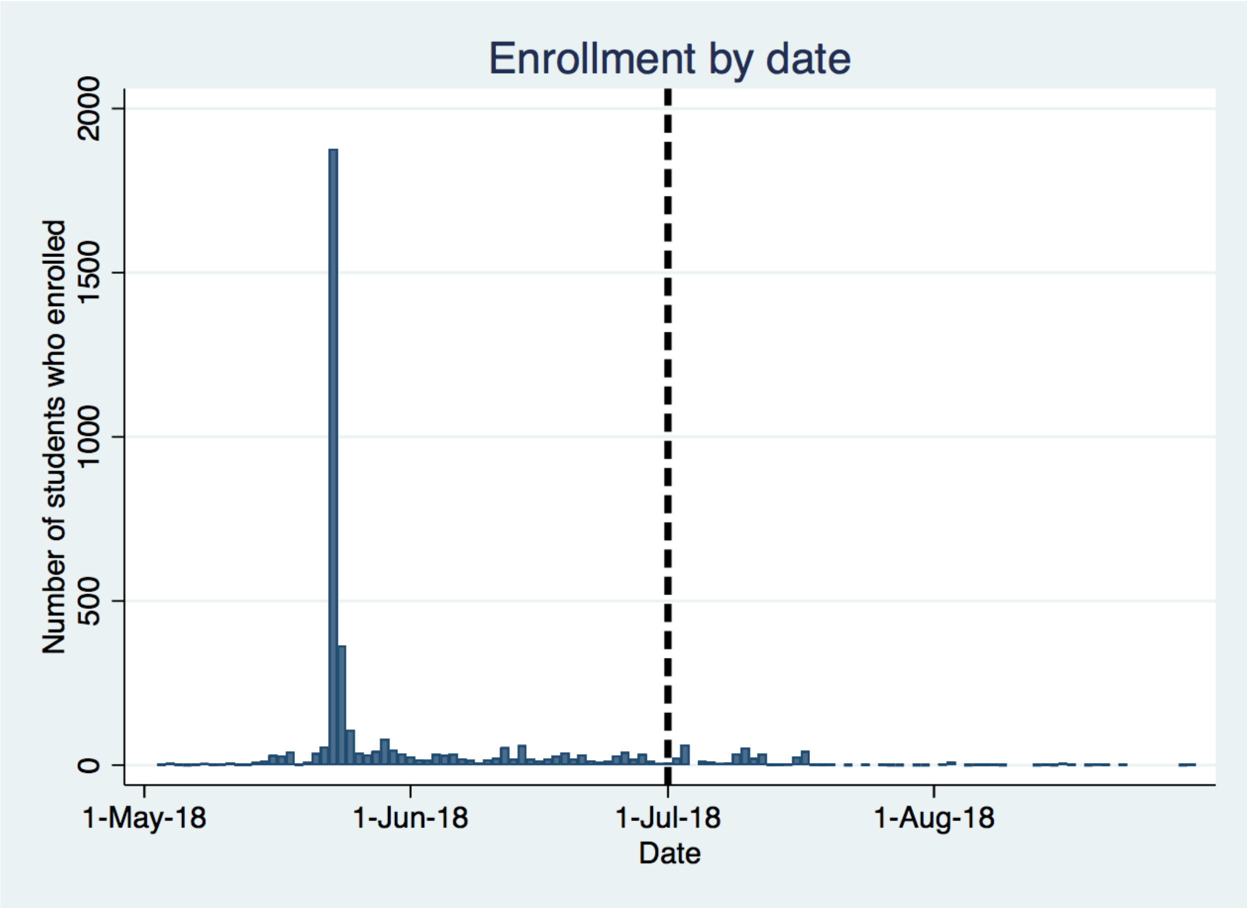

Figure 1. Enrollment at ECU before and after the randomization

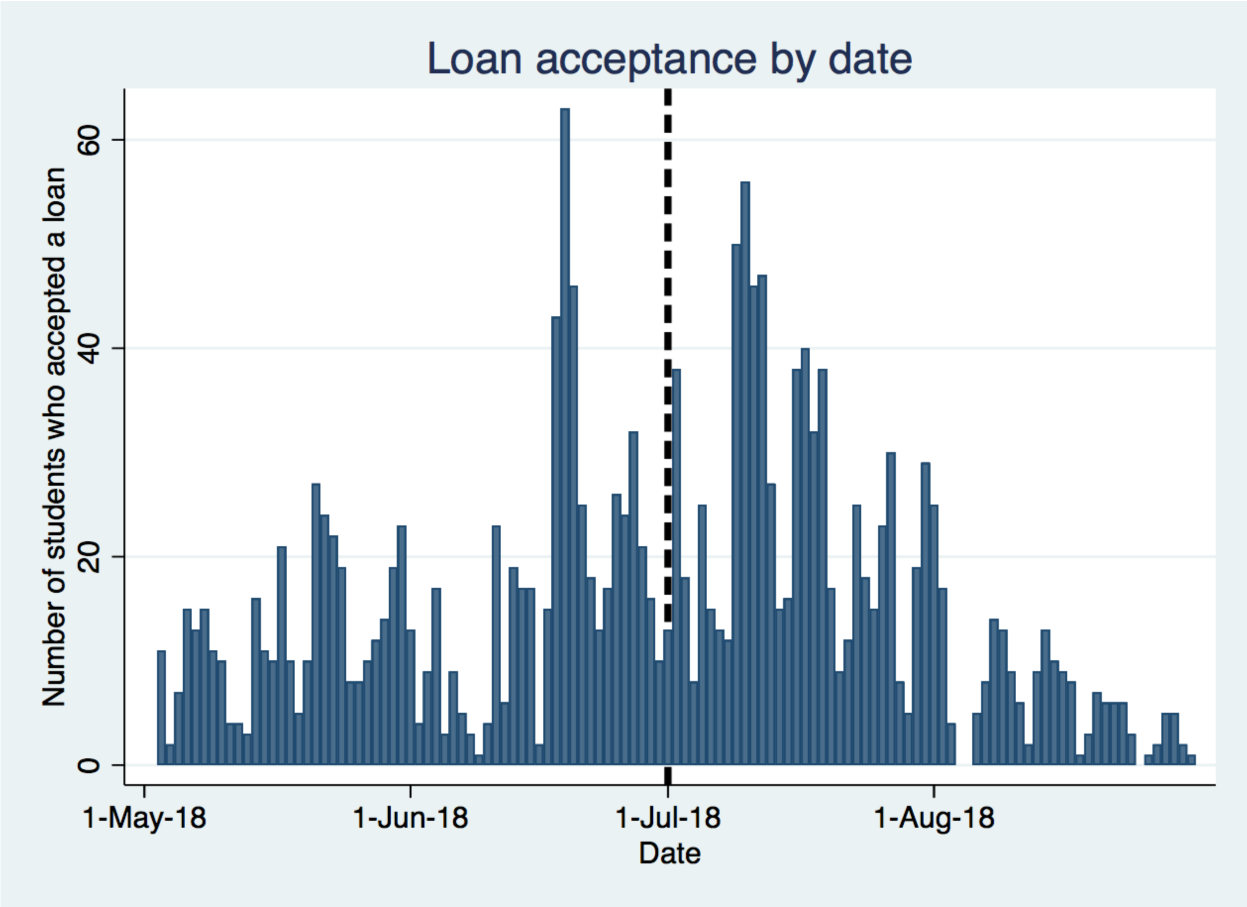

Figure 2. Loan acceptance at ECU before and after the randomization