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The effects of a goal-framing and need-supportive app on undergraduates' intentions, effort, and achievement in mobile science learning

Lucas M. Jeno[a,*], Ulrich Dettweiler[b], John-Arvid Grytnes[c]

[a] Department of Education, University of Bergen, Norway. Postal Address: Postbox 7807, 5020, Bergen, Norway
[b] Department of Cultural Studies and Languages, University of Stavanger, Norway. Postbox 8600, 4036, Stavanger, Norway
[c] Department of Biological Sciences, University of Bergen, Norway. Postal Address: Postbox 7803, 5020, Bergen, Norway

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ABSTRACT

In this study we investigate the effect of manipulating intrinsic goals, relative to extrinsic goals, in a mobile learning tool and traditional textbook for biology students. Using Self- Determination Theory, we hypothesized that framing intrinsic goals in a need-supportive mobile learning app would enhance motivation, intentions, effort, and achievement, relative to extrinsic goals in a traditional tool (textbook). We randomized 128 undergraduate students learning to identify species in this 2 × 2 experiment. Using Bayesian analyses, results show a credible interaction effect between the mobile app and intrinsic goal-framing for intentions and identified regulation. For effort and achievement, the main effect of mobile learning is credible with substantial effect sizes. We argue that these findings are due to the need-supportive features within the mobile app and need-satisfying experience of pursuing intrinsic goals. For intrinsic motivation and amotivation, however, extrinsic goal-framing and intrinsic goal-framing, respectively, are credible and positive main effects, which is unexpected. More research is needed to investigate if this contradictory finding is replicated by others, or if students are pursuing extrinsic goals for autonomous motivation. Bayesian multigroup path analysis found across both groups that identified regulation predicted intentions, and intrinsic motivation predicted effort and achievement. For the extrinsic goal-framing group, amotivation predicted achievement, identified regulation predicted effort and achievement, and intrinsic motivation negatively predicted intentions. The results of our study provide theoretical implications for how goal-framing energizes different types of motivation within the mLearning context, and how manipulation within technology may have a differential effect on motivation than a physical agent.

1. Introduction

The ability to correctly identify species has decreased in recent years and more students are becoming species illiterate (e.g., Skarstein & Skarstein, 2020). This trend is alarming given the threats to global biodiversity due to human actions (Sala et al., 2000; Steinbauer et al., 2018). Hand-in-hand with this alarming development, as society gets wealthier, environmentally responsible attitudes diminish (Kasser, 2009). For instance, a meta-analysis by Hurst et al. (2013) has shown that holding materialistic goals/values

* Corresponding author.
E-mail addresses: Lucas.Jeno@uib.no (L.M. Jeno), ulrich.dettweiler@uis.no (U. Dettweiler), Jon.Grytnes@uib.no (J.-A. Grytnes).

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predicts fewer ecological attitudes and behaviours. However, the promise of technological solutions has given optimism in terms of facilitating the motivational and behavioural processes concerning environmental attitudes such as learning about biodiversity and ecosystems (Cheng et al., 2019; Midden et al., 2007; Wheaton et al., 2016). For instance, "framing" goals within technology to influence motivational processes may be central for a student to become more species literate and to encourage more environmentally friendly attitudes (Lindenberg & Steg, 2013). Hence, creating optimal goals within technology to support students' motivation and behavioural intentions to learn about species and biodiversity is an important line of research. A recent study from New Zealand suggested that technology can be used as a mechanism to facilitate an increase in ecological literacy, indigenous knowledge, and pro-environmental behaviours (Reihana et al., 2019), but evidence on this topic is still sparse.

To address these challenges and limitations in the literature, we apply the motivational theory of Self-Determination Theory (SDT; Ryan & Deci, 2017) to understand how technological solutions can facilitate motivational drivers towards internalizing the value of future environmental efforts and behavioural intentions. Thus, the main aim of this study is to extend the previous literature and investigate how goal-framing in a mobile learning (mLearning) environment can enhance motivation towards learning about species and biodiversity and behavioural intentions in a higher education context. SDT could be an especially useful framework to study learning and behavioural intentions due to its differentiation of quality of motivation, the interpersonal context impact on behaviour, and the specification of how the internalization process affects cognition and behaviour (Pelletier, 2002; Ryan & Deci, 2017). Moreover, using a well-established theoretical framework to understand how mLearning impacts motivation and learning is important given the lack of such integration of theory in the increasing mLearning research (Bernacki et al., 2020).

1.1. *Motivation, mLearning, and achievement*

SDT is a macro-theory of human motivation and wellness and has been employed in a range of domains including healthcare (Ryan et al., 2008), work organization (Deci et al., 2017), and parenting (Joussemet et al., 2008). Recently, there has been attention on applying the motivational principles of SDT to ecological sustainability and pro-environmental attitudes (Kasser, 2016; Pelletier, 2002, ; Pelletier & Sharp, 2008) and technology (Calvo & Peters, 2014; Rigby & Ryan, 2017). Central to SDT applied to technology in general, is that technological designs that are based on psychological need-satisfaction enhance motivation and human functioning (Peters et al., 2018). Specifically, technology that supports the psychological needs for autonomy (feeling agency within the technology), competence (feeling effective in interactions with the technology), and relatedness (connecting with others and feeling belongingness when using the technology) have a positive impact on human motivation and behavioural outcomes (Ryan & Deci, 2002, 2017). Satisfaction of the basic psychological needs manifests as more autonomous, relative to controlled, motivation (Ryan & Deci, 2017). Specifically, intrinsic motivation (i.e., doing an activity for its inherent satisfaction) and identified regulation (i.e., doing an activity out of importance and value) are considered autonomous forms of motivation, whereas external regulation (i.e., doing an activity because of an external contingency) and amotivation (i.e., lacking intentionality, value, and interest to do an activity) are considered controlled forms of motivation.

There have been few studies investigating how goal-framing in technology enhances motivation, learning, and intentions. There has been, however, research in adjacent areas that provide support for our hypotheses. For instance, Osbaldiston and Sheldon (2003) found that university students' perception of an experimenter as autonomy supportive predicted well-internalized self-selected goals, which in turn predicted goal performance and future intentions to attempt pro-environmental goals. Similarly, research has shown that autonomously and controlled motivated pro-environmental behaviours predict easy behaviours, but only autonomous motivation predict difficult behaviours (Aitken et al., 2016). Similar results were reported by Green-Demers et al. (1997). In a recent study on perceptions around vegetable intake, Smit et al. (2019) found that an autonomy supportive online intervention increased participants relevance, mainly explained by choice and autonomy.

Research on mLearning, defined as "learning across multiple contexts, through social and content interactions, using personal electronic devices" (Crompton, 2013, p. 4), has increased in recent years (Bernacki et al., 2020) and, in general, research shows that use of mLearning technology in courses increases enjoyment (Chao, 2019), attention (Merayo et al., 2018), and learning (Halton & Cartwright, 2018; Hartman et al., 2019; Wu, 2018). There are clearly many learning benefits of using mLearning technology for learning. However, experimental research on motivation and mLearning, has been little and not grounded in motivational theory (Crompton & Burke, 2018; Crompton et al., 2017). The use of mLearning has the potential to provide learning opportunities such as authentic learning (tasks related to the immediate learning goals), situated learning (learning takes place in the surroundings applicable to the learning), and context-aware learning (learning is informed by the history and the environment) due to its affordances, accessibility, portability, and educational benefits (Crompton & Burke, 2018; Hashemi et al., 2011). In one of the first studies on mLearning using a SDT framework, Jeno, Grytnes, et al. (2017), found that an mLearning app for species identification enhanced students' perceived competence and intrinsic motivation, relative to a textbook. Intrinsic motivation in turn enhanced students' achievement. Presumably, this effect was accounted for by satisfaction of the need for autonomy and competence provided in the mobile app design. Similar results were found in a pre-test/post-test design among biology students in which a need-supportive mobile app decreased negative affect from pre-test to post-test, whereas a textbook increased negative affect (Jeno, Adachi, et al., 2019).

In addition to a need-supportive design, the framing of content in technology may have a differential impact on motivation, behaviour, and learning. According to SDT (Ryan & Deci, 2017), teaching activities may be framed in terms of intrinsic (e.g., community, growth, health) versus extrinsic (e.g., wealth, fame, image) goals which have a differential impact on motivation, behaviour, and learning (Vansteenkiste et al., 2006). Intrinsic goal-framing, relative to extrinsic goal-framing, is associated with positive outcomes due to its satisfaction of the basic psychological needs. This has been supported in numerous studies. For instance, Vansteenkiste, Simons, Lens, Soenens, et al. (2004) conducted a study in which pre-school teachers read a text on recycling following an intrinsic goal framing (contribute to society), an extrinsic goal (save money), or a double goal condition (both intrinsic and extrinsic goal). Results show that students with an intrinsic goal-framing reported less stress during participation, more mastery, and more conceptual understanding, compared to students in the double goal-framing. Further, the double-goal framing provided more adaptive outcomes than an extrinsic goal-framing, suggesting that content of the goal is important. Vansteenkiste, Simons, Lens, Sheldon, et al. (2004) conducted a set of three experiments involving students learning some text material. Students were randomized to either intrinsic (community) or extrinsic (wealth) goal-framing and crossed with an autonomy-supportive or controlling learning climate. Results showed that intrinsic goal-framing in an autonomy-supportive climate enhanced deep processing of learning material, less superficial processing of material, autonomous motivation, and performance (Vansteenkiste et al., 2004a, 2004b, 2004c, study 1). Similar results has been found in an exercise context (Vansteenkiste et al., 2005; Vansteenkiste, Simons, Soenens, et al., 2004) and longitudinally (Hope et al., 2019). In a recent study in social marketing, Lee and Pounders (2019) found that the effect of intrinsic goals, relative to extrinsic goals, enhanced behavioural intentions. This effect was partly mediated by autonomous motivation and message persuasiveness. In summary, studies have generally found that intrinsic goals, relative to extrinsic goals, promote autonomous motivation, learning, and well-being. However, of the reviewed literature, no studies have been found that experimentally manipulate goal-framing in an mLearning context.

1.2. *Present study*

Experimental research on mLearning and motivation using theoretical approaches is in its infancy (e.g., Bernacki et al., 2020; Crompton & Burke, 2018) and not many studies have addressed mLearning and motivation through the theoretical lenses of SDT. Hence there is a need for more studies investigating these issues. Of the few studies reviewed, the research seems to find that use of mLearning enhances need-satisfaction (Jeno, Vandvik, et al., 2019; Nikou & Economides, 2018), autonomous motivation (Jeno, Grytnes, et al., 2017), and behavioural intentions (Nikou & Economides, 2017; Yang et al., 2018). In our literature review, we only found three studies that used goal aspirations in their studies. Of the first, Choi et al. (2014) conducted content analyses of 175 smoking cessation apps and found that 25% of the apps had extrinsic goals (gain or loss features) whereas only 3% had intrinsic goals. Of the apps that had at least one SDT feature that tapped each need for autonomy, competence, and relatedness, four were among the top five, and contained need-supportive features aiding one's quitting plan and managing it (autonomy), providing tips and strategies (competence), and sharing on social media (relatedness). Using a qualitative approach, Peters et al. (2017) reported that intrinsic life goals for managing young peoples' asthma could be features included in mobile apps for asthma management. James et al. (2019) investigated how exercise goals are embedded in fitness technology, and found in a mTurk sample that intrinsic exercise goals positively predicted data management features such as data collection, data analysis, progress updates, and information searching, whereas extrinsic exercise goals predicted control features such as rewards, reminders, and goal management, and social interaction features such as data sharing, encouragement, competition, comparison, and coaching.

We wish to help close the gap in the literature and investigate how mLearning design might be improved by framing the goal of the task as either intrinsic or extrinsic to create autonomous motivation and sustained behavioural outcomes. Given the few studies on this topic, our contribution is important for understanding how goal-framing in an mLearning design impacts students' motivation and learning. Moreover, by using SDT and proposing hypotheses based on theory, we can further understand the mechanism through which goal-frames embedded within mLearning technology might affect motivation and learning. Further, our contribution is also important because it could provide new understanding of the potential mechanism of goal-framing in mLearning technology, and provide theoretical advancements. Hence, in this study, the main research question we wish to investigate is: "Does framing an intrinsic goal within a need-supportive mobile application enhance students' motivation, intentions, effort, and achievement for learning about biodiversity, relative to an extrinsic goal with a non-need-supportive textbook?".

1.2.1. *Intrinsic and extrinsic goal-framing*

To investigate our research question on the impact of goal-framing and mLearning, we draw on the conceptualization of goal-framing within SDT. In contrast to match hypothesis on goal-framing (e.g., Schneider, 1987) and Levin et al. (1998) typology on framing effects, SDT suggests that all goals are not created equal (Ryan et al., 1996). Hence, in the present study we manipulate participants' goal content for species identification. Specifically, the identification processes is introduced (framed) in terms of the goal it will lead to (Ryan & Deci, 2017; Vansteenkiste et al., 2009).

In this study, we framed the goals in terms of future likelihood of attaining an extrinsic or intrinsic goal (Kasser, 2019). For extrinsic goal-framing, we manipulated the likelihood of attaining financial success (to be wealthy and materially successful). For intrinsic goal-framing, we manipulated the likelihood of attaining community feeling (to improve the world through activism or generativity). We followed the work by Vansteenkiste, Simons, Lens, Sheldon, et al. (2004) and Vansteenkiste, Simons, Soenens, et al. (2004) when developing our instructions for goal-framing. Vansteenkiste, Simons, Lens, Sheldon, et al. (2004) provided participants with a text about recycling which manipulated an intrinsic goal (contributing to the community) and an extrinsic goal (financial success) for future attainment. Vansteenkiste, Simons, Soenens, et al. (2004) provided participants with a text on Taiboo exercises which manipulated an intrinsic goal (health) and an extrinsic goal (physically attractive to others) for future attainment. The length of the goal-framing in both conditions in the present study are the same length in order to reduce visible differences for the students and prevent them from noticing that there were different experimental conditions, following Vansteenkiste, Simons, Lens, Sheldon, et al. (2004) and Vansteenkiste et al. (2008).

We chose species identification as a learning activity to manipulate because this is a key skill that biology students must learn. There are several important species that need to be learned and engagement varies with the extent that they are perceived as interesting by students. The identification of sedges (*Carex*) is often perceived as difficult and therefore less interesting and motivating for biology students to learn, but it is a species-rich group with many ecologically important species and they often function as indicator species for ecological conditions (Jeno, Grytnes, et al., 2017). We chose the context of biology and environment because living sustainably is important for the environment and, according to Kasser (2009, p. 176), "creates behaviours that satisfy psychological needs".

1.2.2. Identification tools

Traditionally, species identification is conducted through a textbook Flora (Lid & Lid, 2005). When identifying with these textbooks, a student starts hierarchically with the highest taxonomic characteristics of the species and moves through 8–10 characteristics before ending up with a suggested species. The characteristics in the textbook are answered dichotomously, meaning that the student must decide upon one of two suggestions within a characteristic before moving on to the next characteristic. Although the students can correctly identify species, this process is difficult to fully grasp and comprehend for undergraduate students and may be perceived as less need-supportive due to its very structured form and lack of support.

In contrast, in the mLearning tool ArtsApp (University of Bergen, 2017), the identification process is more need-supportive in that it is dynamic in nature and provides more choice and feedback during the identification process. In this mobile app, a student has the choice to start with any of the characteristics without following any specific structure. The mobile app provides lively pictures, explanations of the identification process, and a user-friendly interface. Moreover, the mobile app provides feedback on eliminated species, how many potential species are left, and information on the characteristics. This process of identifying species may be perceived as more need-supportive for the student.

Based on the theoretical propositions of SDT and previous research, we put forth the following hypotheses:

H1. Participants in the intrinsic goal-framing condition using the mobile app will exhibit higher intentions, effort, and achievement.

H2a. Participants in the intrinsic goal-framing condition using the mobile app will exhibit higher intrinsic motivation and identified regulation.

H2b. Participants in the extrinsic goal-framing condition using the textbook will exhibit higher external regulation and amotivation.

H3. Autonomous regulations (i.e., intrinsic motivation and identified regulation) will predict higher intentions, effort, and achievement.

2. Methods

2.1. Participants and procedure

Second-year undergraduate biology students ($n = 128$; 65.3% female; median age 21) were recruited to the study. One participant was removed due to only responding on the achievement test and not responding on the questionnaire, making the final sample size $n = 127$. The participants were drawn from a convenience sample collected from a biology course from two different cohorts. Participants were recruited from a week-long mandatory field course provided by their university. During this field course, the students learn about different species, how to identify them, and how the species interact and depend on each other as part of an ecology course. The participants were asked to participate after the first introductory day, during which the students are introduced to the two different species identification tools – a traditional textbook (Lids Flora: Lid & Lid, 2005) and a mobile app (University of Bergen, 2017) – and shown how to collect different species. The experimentation period lasted for three days.

The experiment took place in a natural field setting where students were brought by a research assistant, blind as to the study hypotheses, in groups of 5–8 students to a classroom to participate in the experiment. A research assistant was chosen in order to reduce the bias from the researchers analysing the data. The participants were seated and handed an envelope with a questionnaire containing information on the study. The students received general information about the aim of the study which was to understand students' attitudes towards species identification and learning intentions. The participants were told that participation was voluntary and that they could withdraw at any time. Participants were also told that their answers would be anonymous and treated confidentially. Participants were then randomized into a 2(Goal-framing: intrinsic vs. extrinsic goal) x 2(Identification tool: mobile app vs. textbook) experimental design. Table 1 summarizes the distribution of participants in the experimental conditions.

Students randomized into the intrinsic goal-framing were given the following goal-framing message:

Table 1
Cell distribution of participants in the experimental conditions.

Identification tool	Goal-framing	N	(%)
Mobile app	Intrinsic	34	51.5
	Extrinsic	32	48.5
	$n_{mobile\ app}$	66	100.0
Textbook	Intrinsic	31	50.8
	Extrinsic	30	49.2
	$n_{textbook}$	61	100.0
N_{total}		127	100.0

You are now going to identify sedges. Being able to identify species is a necessary skill to learn as a biologist. It will not only equip you with important skills, but will also be an important prerequisite for understanding ecology and the interplay between species, and enabling you to provide important knowledge of the species' distribution and conservation of biodiversity. So, try your best. You can go forward and choose from 3 to 10 sedges. On the next page is part 1 which is a list of 10 areas where you can write down the sedges you chose.

Students randomized into the extrinsic goal-framing were given the following goal-framing message:

You are now going to identify sedges. Being able to identify species is a necessary skill to learn as a biologist. It will not only equip you with important skills to improve your grades in this course, it will also enable you to get high-paying jobs after your degree and compete for the most attractive jobs. So, try your best. You can go forward and choose from 3 to 10 sedges. On the next page is part 1 which is a list of 10 areas where you can write down the sedges you chose.

Participants were then crossed with *Identification tool*, that is, the participants used either the mobile app or the traditional textbook as a species identification tool. Lastly, participants were provided with a post-experimental questionnaire measuring different motivational and behavioural constructs. After the students had terminated the experiment, the research assistant informed the students that the information provided initially was part of an experiment and that they could contact the first author for any questions or concerns. No students contacted us for any query. The students were then thanked for participating in the experiment.

3. Measures

3.1. Extrinsic motivation

We employed the Situational Motivation Scale (SIMS; Guay et al., 2000) to measure students' Amotivation (4 items; "There may be good reasons for identifying species with this identification tool, but personally I don't see any"), External regulation (4 items; "Because it is something that I have to do"), and Identified regulation (4 items; "Because it is for my own good to identify species with this identification tool") for species identification. The participants were asked to respond on a 7-point Likert-scale ranging from 1 (not true at all) to 7 (very true). The SIMS has previously been shown to be valid and reliable among a sample of higher education students (Guay et al., 2000; Jeno, Raaheim, et al., 2017). For the present study, Cronbach's alpha values were found for Amotivation ($\alpha = 0.86$), External regulation ($\alpha = 0.60$), and Identified regulation ($\alpha = 0.75$).

3.2. Intrinsic motivation

We employed the 7-item Interest/Enjoyment subscale within the Intrinsic Motivation Inventory (IMI; Ryan, 1982) to measure participants' Intrinsic motivation for identifying species. An item example is "I enjoyed identifying species with this identification tool". The participants responded on a 7-point Likert-scale ranging from 1 (not true at all) to 7 (very true). The factor structure of the IMI was validated by McAurley et al. (1989), and has been used in mLearning studies among biology students and shown to be reliable in higher education (e.g., Jeno, Grytnes, et al., 2017). In the current study, Cronbach's alpha of .94 was achieved for Intrinsic motivation.

3.3. Intentions

A 5-item scale was used to measure participants' future Intentions for learning more about species. This scale is an adapted version from Hardre and Reeve (2003) and Jeno et al. (2018), and has been shown to be reliable with acceptable Cronbach's alpha and appropriate for a higher education context. Participants responded on a 7-point Likert-scale ranging from 1 (not at all true) to 7 (very true). An item example is "I intend to spend more time understanding species distribution". We found a satisfactory internal consistency in the present study for the Intentions scale (Cronbach's $\alpha = 0.83$).

3.4. Effort

We employed the Effort/Importance subscale within the Intrinsic Motivation Inventory (IMI; Ryan, 1982) to measure the students' Effort in relation to species identification. The subscale consists of five items ("I put a lot of effort into this activity"), and the participants answered on a 7-point Likert scale ranging from 1 (not at all true) to 7 (very true). The effort subscale has been shown to be both reliable and valid (McAurley et al., 1989) and used among higher education students (Yang et al., 2011). In the present study, we achieved a Cronbach's alpha for effort of 0.87.

3.5. Achievement

Achievement was measured via a species identification score. A number of *Carex* species were selected from a list of pre-determined species hand-picked by a research assistant unaware of the study's hypotheses. Each species was allocated to a plastic bag and given a number. The participants then attempted to identify the species and wrote down the name of the species in a field on the questionnaire that corresponded to the number on the plastic bag. The results of the achievement test were assessed by a research assistant blind to the hypotheses. Correct identification of a species was awarded 5 points, identification of a very similar species was awarded 4 points, a similar species was given 3 points, and a slightly similar species 1 point. Incorrect species were given 0 points. A total Achievement composite score was given to each participant (see Jeno, Grytnes, et al. (2017) and Jeno, Adachi, et al. (2019)) for a similar approach). Given the variability of number of species chosen, we adjusted our Achievement variable by dividing it by the number of species chosen.

3.6. Analytical strategy

3.6.1. The bayesian approach

For the statistical analyses, we chose a Bayesian approach in order to mitigate overfitting. For hypotheses H1 and H2, we set up 2 × 2 ANOVAs in order to investigate the interaction effects between identification tools and goal framing conditions. Therefore, we used prior distributions informed by our expectations of the variance explained by the predictor variables in the respective models, expressed by R^2 (Goodrich, 2019). A beta prior is set on R^2, which has two shape parameters, a and b. The first (a) is specified as a hyperparameter and equals half the number of predictors. The second shape hyperparameter (b) represents the location specification of R^2 in an interval [0,1], and since the location specification of R^2 hinges on the covariance matrix, the shape parameter grows with smaller R^2. With smaller prior correlations among the outcome and predictor variables, the prior density for the regression coefficients approaches zero rather than being equally distributed over the whole range of values (Gabry & Goodrich, 2019; Zografos, 1999). Thus, prudent and informed specification of R^2 should lead to credible results in the models. For hypothesis H3, we chose a multivariate approach and fit a multi-group Bayesian path analysis with “goal framing” as the split variable. Since the External regulation scale showed rather low internal reliability, we chose to drop it for the path analysis. For the regressions of the identification tool on the three remaining motivational regulations, we used a vaguely informative prior N(0, 0.5), and an even slightly flatter prior N(0, 0.8) for the regressions of the motivational regulations on effort, intentions, and achievement to mitigate overfitting. Those prior choices can be compared to the R^2 priors used for the ANOVAs. All models have been tested for their respective prior sensitivity compared to the reference model with uninformed priors (Gelman & Hill, 2007), and no problematic bias on the regression coefficients could be detected. This makes the results comparable to the more common frequentist null-hypothesis testing framework.

All statistical analyses were conducted using the statistical program R version 3.5.2 (R Core Team, 2018) and the open source software package JASP 0.11.1 (JASP Team, 2019), which is a graphical user interface built on R. For data preparation along with preliminary analyses such as descriptive statistics and Cronbach’s alpha for reliability testing we used the following packages: “apaTables” (Stanley, 2018), “memisc” (Elff, 2019), “multicon” (Sherman, 2015), and “psych” (Revelle, 2018). For the Bayesian ANOVA’s we employed “rstanarm” package (Goodrich et al., 2018) and explored the results using the interactive program “shinystan” (Gabry, 2018). For the ANOVAs, we adjusted the prior specification on our expectations of the variance explained by the factors for the whole model with $R^2 = 0.1$.

The path analysis for hypothesis H3 was run in “blavaan” (Merkle & Rosseel, 2018).

For each model, we performed four MCMC chains of iterations with 40 000 simulations. Convergence of the MCMC chains and model fit was assessed with graphical posterior predictive checks for observed vs average simulated values by using the given functionalities in the package “shinystan” for the ANOVAs and “coda” (Plummer et al., 2006) for the path analysis. Scale reduction factors $\widehat{R}$ below 1.1 indicated good convergence (Brooks & Gelman, 1998). WAIC (Watanabe-Akaike information) and loo (Leave-one-Out) criteria were used to compare relative model fit between the informed prior and the reference model, as suggested by Gelman et al. (2014). For the path analysis, model fit was additionally assessed using the posterior predictive p-value (van de Schoot et al., 2014), with $ppp > 0.15$ indicating adequate, and $ppp \approx 0.5$ indicating excellent model fit. To interpret the effects sizes ES in the statistical models, we followed Gelman and Carlin (2014) who consider a magnitude of ES = Mean/SD > 1.96 as substantial, where Mean is the posterior estimate and SD is the standard deviation.

4. Results

4.1. Preliminary analysis

Descriptive statistics, presented in Table 2, show that all variables are within the acceptable range, and no variables show violation of normality. Bayesian correlational analyses are all in the expected direction (see Table 3). Specifically, Intentions is positively related to Effort and Identified regulation, and negatively related to Amotivation. Effort is positively related to Achievement, Intrinsic motivation and Identified regulation, and negatively related to Amotivation. Achievement is positively related to Intrinsic motivation.

Table 2
Descriptive statistics of the study variables.

Variables	n	mean	SD	min	max	range	skew	kurtosis
Intentions	127	5.32	1.24	1.00	7	6.00	-.98	.87
Effort	127	4.45	1.25	1.40	7	5.60	-.02	-.41
Achievement	127	1.43	1.31	.00	5	5.00	0.77	−0.03
Intrinsic motivation	125	4.26	1.61	1.00	7	6.00	-.39	-.82
Identified regulation	110	4.32	1.24	1.25	7	5.75	-.15	-.45
External regulation	108	4.24	1.21	1.25	7	5.75	.04	-.67
Amotivation	117	2.46	1.25	1.00	7	6.00	1.19	1.38

Table 3
Bayesian Pearson correlations between study variables.

	1	2	3	4	5	6	7
1. Intentions	–						
2. Effort	.336***	–					
3. Achievement	.181	.372***	–				
4. Intrinsic motivation	.181	.449***	.327***	–			
5. Identified regulation	.549***	.432***	.194	.557***	–		
6. External regulation	-.009	-.168	.015	-.431***	-.133	–	
7. Amotivation	-.397***	-.393 ***	-.186	-.633***	-.736***	.333**	–

Note: *$BF_{10} > 10$, **$BF_{10} > 30$, ***$BF_{10} > 100$.

Finally, for the motivational regulations, the correlational matrix shows that Intrinsic motivation is positively related to Identified regulation, and negatively related to External regulation and Amotivation. Identified regulation is not credibly related to External regulation, but negatively related to Amotivation. External regulation and Amotivation are positively related.

We conducted several Bayesian independent t-tests to investigate if there were systematic differences between gender across our study variables. We found no evidence for these (all $BF_{10} < 1.1$), hence we collapsed gender across all our variables for subsequent analyses.

4.2. Primary analysis

4.2.1. Interaction effects of the experimental conditions on intentions, effort, and achievement (H_1)

To investigate the interaction effect between our experimental conditions on Intentions, Effort, and Achievement (hypothesis 1), we conducted a 2 × 2 Bayesian ANOVA for each outcome variable (Table 4). For Intentions, we find support for the interaction effect between the two factors with an 80% credibility, although the magnitude of the effect is insubstantial. This suggests that we can with an 80% credibility be confident that students using the mobile app in the intrinsic goal-framing have slightly higher intentions to learn more about species. No credible main effects (*Goal-framing*: intrinsic vs. extrinsic goal-framing or *Identification tool*: mobile app vs. textbook) are found.

For Effort, no interaction effect is credible. We find, however, support for the main effect of Identification tool with a credibility of 95% and a substantial effect size (mean/SD = 2.58). This suggests that students using the mobile app, compared to the textbook, exhibited more effort. Finally, for Achievement, no interaction effect is credible. We find one credible result for the main effect of Identification tool on Achievement at the 80% level suggesting that students using the textbook scored lower on the achievement test compared to students using the mobile app. The effect size for this finding is small.

4.2.2. Interaction effects of the experimental conditions on motivational regulations (H_2)

To investigate the interaction effect between our experimental conditions on the different motivational regulations (hypothesis 2a and 2 b) we performed a 2 × 2 Bayesian ANOVA for each of the motivational regulations (Table 5). For Intrinsic motivation, no credible interaction effect is found. We find two credible main effects at the 95% level with substantial effect sizes. For Identification tool, we find that students using the mobile app, compared to the textbook, exhibited higher Intrinsic motivation. For goal-framing, we find that students in the extrinsic goal-framing exhibited higher Intrinsic motivation. For Identified regulation, we find an 80% credible interaction effect suggesting that students using the mobile app with an intrinsic goal framing reported higher Identified regulation, although this effect size is insubstantial. Furthermore, we find a main effect for Goal-framing that is credible at 95%. This suggests that students with extrinsic goal-framing reported higher Identified regulation. For External regulation, no credible interaction effect is found. We find, however, a credible effect for Identification tool with a substantial effect size. This suggests that students using the

Table 4
2 × 2 bayesian ANOVA on intentions, effort, and achievement.

	Total R^2	Intercept	σ(model)	Mean (*SD*)	ES	2.5%–97.5%
Intentions	.04	5.39	1.23			
Identification tool				-.17 (.30)	-.56	-.76–.42
Goal-framing				-.26 (.30)	-.86	-.85–.33
Identification tool * Goal-framing				.57 (.42)	1.35†	-.25 – .1.39
Effort	.10	4.16	1.2			
Identification tool				.75 (.30)	2.58***	.16–1.32
Goal-framing				-.11 (.29)	-.37	-.69–.47
Identification tool * Goal-framing				-.13 (.41)	-.32	-.93–.69
Achievement	.11	.15	1.21			
Identification tool				-.46 (.37)	−1.24†	−1.18–.27
Goal-framing				-.14 (.27)	-.51	-.69–.39
Identification tool * Goal-framing				.39 (.40)	.97	-.40–1.18

Note: All models converged well with Rhat values < 1.1.*** credible at 95% level, ** credible at 90% level, * credible at 85% level, † credible at 80% level. ES = Effect sizes >1.9 are considered substantial. Identification tool (mobile app = 1, textbook = 0), Goal-framing (intrinsic = 1, extrinsic = 0).

Table 5
2 × 2 Bayesian ANOVA on motivational regulations.

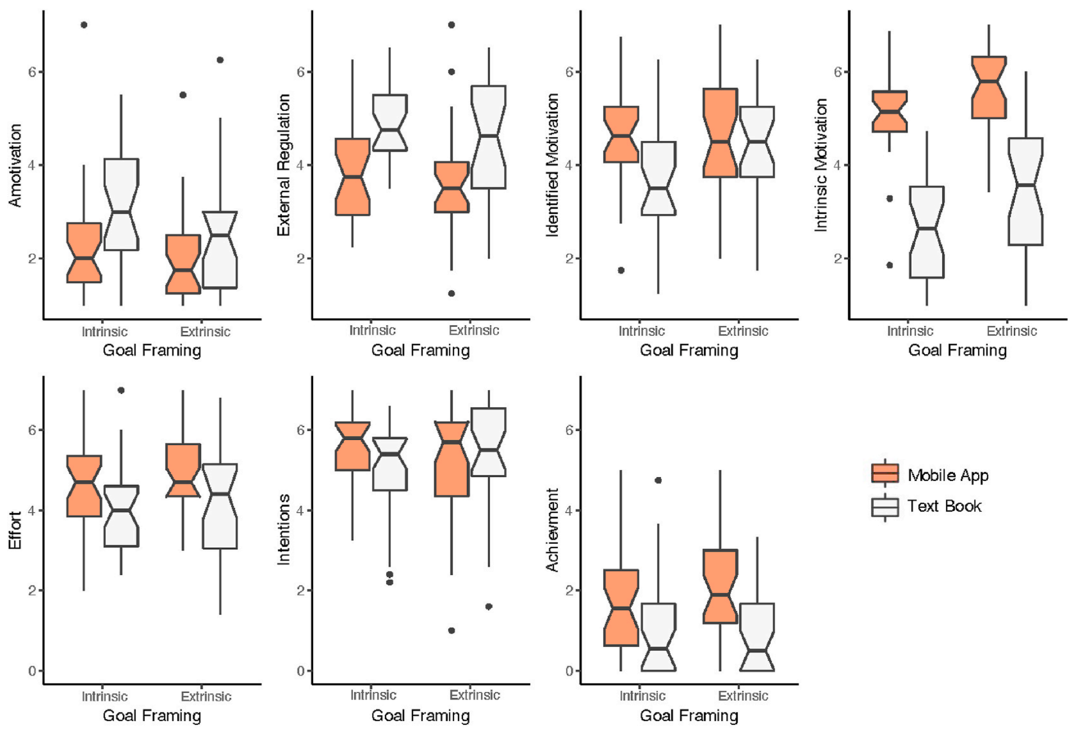
	Total R^2	Intercept	σ(model)	Mean (*SD*)	ES	2.5%–97.5%
Intrinsic motivation	.51	3.54	1.12			
Identification tool				1.95 (.28)	6.96***	1.39–2.50
Goal-framing				-.85 (.28)	−3.04***	−1.41–−.29
Identification tool * Goal-framing				.44 (.39)	1.13	-.33–1.20
Identified regulation	.12	4.34	1.18			
Identification tool				.32 (.31)	1.03	-.29–.92
Goal-framing				-.66 (.31)	−2.13***	−1.26–−.06
Identification tool * Goal-framing				.58 (.43)	1.35†	-.27–1.41
External regulation	.15	4.55	1.13			
Identification tool				-.80 (.30)	−2.67***	−1.39–−.23
Goal-framing				.26 (.30)	.87	-.33–.85
Identification tool* Goal-framing				-.06 (.42)	-.14	-.89–.77
Amotivation	.12	2.47	1.19			
Identification tool				-.43(.30)	−1.43	−1.00–.17
Goal-framing				.65 (.31)	2.10***	.04–1.25
Identification tool* Goal-framing				-.41 (.42)	-.98	−1.24–.42

Note: All chains in the Bayesian ANOVA converged well with Rhat values < 1.1. *** credible at 95% level, ** credible at 90% level, * credible at 85% level, † credible at 80% level. Effect sizes >1.9 are considered substantial. Identification tool (textbook = 0, mobile app = 1), Goal-framing (extrinsic = 0, intrinsic = 1).

textbook, as opposed to mobile app, reported higher External regulation. Finally, for Amotivation, no interaction effect is found. One credible main effect is found, which suggests that students with an intrinsic goal-framing reported higher Amotivation compared to students with an extrinsic goal-framing. This effect size is substantial. See Fig. 1 for a visualization of the motivational regulations across the study conditions.

4.2.3. Differential effect of the motivational regulations on intentions, effort, and achievement (H_3)

Lastly, to investigate the differential effect of the motivational regulations on Intentions, Effort, and Achievement (hypothesis 3),



Note: Minimum value for all variables is 1 and maximum 7, except for achievement where minimum value is 0 and maximum is 27.

Fig. 1. Study variables by each of the study conditions.

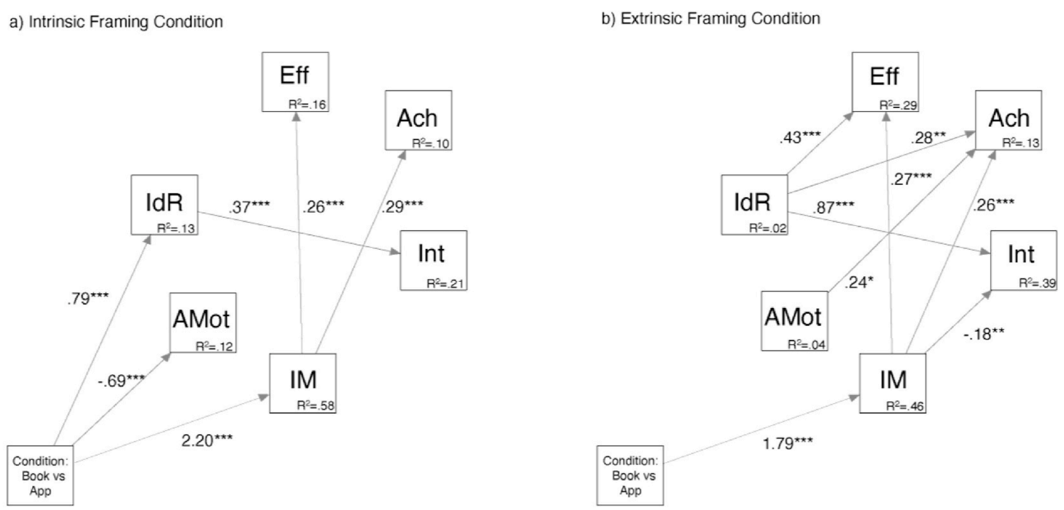
we performed a multi-group Bayesian path analysis with goal-framing as the split-variable. We specified condition (textbook vs. mobile app) as the exogenous variable, the motivational regulations as mediators, and Intentions, Effort, and Achievement as endogenous variables. The path analysis with vaguely informed priors showed acceptable model fit, PPP = .167, LOOIC = 2405.28, and WAIC = 2403.25, and the results are visualized in a path diagram in Fig. 2 and presented in Table 6. Specifically, the results showed that in both the goal-framing groups, the mobile app relatively to the textbook, positively enhanced Intrinsic motivation. In the intrinsic goal-framing group, but not in the extrinsic goal-framing group, the textbook reduced Amotivation whereas the mobile app enhanced Identified regulation. In both goal-framing groups, Identified regulation enhanced Intentions, and Intrinsic motivation enhanced Effort and Achievement. In the extrinsic goal-framing group, but not in the intrinsic goal-framing group, Identified regulation was positively related to Effort and Achievement. Interestingly, in the extrinsic goal-framing group, Amotivation was positively related to Achievement, whereas Intrinsic motivation is negatively associated with Intentions.

Further, in the extrinsic goal-framing group, some of the effects are reduced compared to the intrinsic goal-framing group. For example, the effect of the mobile app on Intrinsic motivation is about 35% lower. Whereas in the extrinsic goal-framing group, compared to the intrinsic goal-framing group, the effects of Intrinsic motivation on Effort (7.8%), Identified regulation on Intentions (54.1%), and Intrinsic Motivation on Achievement (4.1%) are increased. Finally, for the intrinsic goal-framing group, the model as a whole predicted 16%, 10%, and 21% of the variance in Effort, Achievement, and Intentions, respectively. For the extrinsic goal-framing group, the model predicted 29%, 13%, and 39% of the variance in Effort, Achievement, and Intentions, respectively.

5. Discussion

The main aim of this study was to extend the previous literature on mLearning, goal-framing, and motivational regulation, and investigate how framing intrinsic goals, relative to extrinsic goals, in a need-supportive mLearning tool, can enhance motivation, Intentions, Effort, and Achievement for learning about biodiversity in a higher education context. The results generally did not support our hypotheses, and although some were supported, some findings were unexpected.

In our first hypothesis, we expected that students in an intrinsic goal-framing using the mobile app would exhibit higher Intentions, Effort, and Achievement. For Intentions, the results from our 2 × 2 ANOVA show a credible, albeit small, interaction effect. This result suggests that the interaction between intrinsic goal-framing (relative to extrinsic) and mobile app (relative to textbook) enhances students' Intentions to learn more about species. This is in line with previous research (e.g., Vansteenkiste et al., 2004a, 2004b, 2004c) and theoretical propositions by SDT that suggest that intrinsic goal-framing and need-support jointly predict beneficial outcomes (Ryan & Deci, 2017). However, given that this effect was small and less credible, future studies need to replicate this result. Regarding Effort, results showed only a significant main effect for identification tool. That is, using the mobile app increased students' effort for species identification, compared to students using the textbook. Finally, for Achievement, only identification tool reached a credible effect, indicating that students using the mobile app, on average, scored higher than students using the textbook. Hence, the results only partly support our hypothesis. These latter findings are in line with SDT (Ryan & Deci, 2017) and supported by similar studies on



Note: ***credible at 95% level, **credible at 90% level, *credible at 85% level
The path diagram displays the unstandardized posterior effect estimates (beta's) in the respective regressions in a) the intrinsic goal framing condition, and b) in the extrinsic goal framing condition. Condition is coded as textbook=0, and mobile app=1. IdR=Identified Regulation, AMot=Amotivation, IM=Intrinsic Motivation, Eff=Effort, Ach=Achievement, Int=Intentions

Fig. 2. The path diagram displays the unstandardized posterior effect estimates (beta's) in the respective regressions in a) the intrinsic goal framing condition, and b) in the extrinsic goal framing condition. Condition is coded as textbook = 0, and mobile app = 1. IdR = Identified Regulation, AMot = Amotivation, IM=Intrinsic Motivation, Eff = Effort, Ach = Achievement, Int = Intentions.

Table 6
Estimates of the regression coefficients from the multi-group path analysis.

DV	Predictor	Mean	(SD)	ES	2.5%	97.5%	Mean	(SD)	ES	2.5%	97.5%	Goal-framing Effect on ES [%]
		Intrinsic goal-framing Group					Extrinsic goal-graming Group					
IM	Cond	2.20	(0.24)	9.20***	1.73	2.66	1.79	(0.26)	6.84***	1.27	2.30	−34.50***
IdR	Cond	0.79	(0.25)	3.15***	0.29	1.28	0.27	(0.26)	1.02	−0.25	0.79	n.c.
AMot.	Cond	−0.69	(0.26)	−2.67***	−1.18	−0.18	−0.30	(0.25)	−1.20	−0.79	0.20	n.c.
Int	IM	−0.01	(0.10)	−0.07	−0.20	0.19	−0.18	(0.11)	−1.64**	−0.40	0.04	n.c.
Int	IdR	0.37	(0.15)	2.48***	0.07	0.67	0.87	(0.16)	5.40***	0.55	1.19	54.07***
Int	AMot.	−0.09	(0.15)	−0.61	−0.39	0.22	0.03	(0.17)	0.16	−0.31	0.36	n.c.
Eff	IM	0.26	(0.11)	2.26***	0.03	0.48	0.27	(0.11)	2.45***	0.06	0.49	7.76***
Eff	IdR	0.19	(0.17)	1.16	−0.13	0.53	0.43	(0.16)	2.67***	0.10	0.75	n.c.
Eff	AMot.	0.05	(0.17)	0.30	−0.27	0.39	0.05	(0.17)	0.28	−0.29	0.39	n.c.
Ach	IM	0.29	(0.14)	2.13***	0.02	0.56	0.26	(0.12)	2.22***	0.03	0.49	4.05***
Ach	IdR	−0.05	(0.21)	−0.25	−0.47	0.35	0.28	(0.16)	1.73**	−0.03	0.60	n.c.
Ach	AMot.	−0.05	(0.20)	−0.24	−0.44	0.35	0.24	(0.17)	1.37*	−0.11	0.58	n.c.

Note: All chains in the Bayesian path analysis converged well with Rhat values < 1.1. *** credible at 95% level, ** credible at 90% level, * credible at 85% level, n.c.: not credible. Effect sizes (ES) > 1.96 are considered substantial. Condition = Cond, Condition (textbook = 0, mobile app = 1), IdR = Identified Regulation, AMot = Amotivation, IM=Intrinsic Motivation, Eff = Effort, Ach = Achievement, Int = Intentions, DV = Dependent Variable.

mLearning and motivation (e.g., Jeno, Adachi, et al., 2019; Jeno, Grytnes, et al., 2017). Specifically, the results suggest that identification tools with need-supportive elements (i.e., the mobile app) increase effort and learning. These effects are due to the support of the basic psychological needs for autonomy and competence embedded within the mobile app.

Results relating to hypothesis 2a and 2 b showed some unexpected findings. For hypothesis 2a, we found two main effects for intrinsic motivation. Mirroring previous studies (Jeno, Adachi, et al., 2019; Jeno, Grytnes, et al., 2017), students using the mobile app, relative to textbook, reported higher Intrinsic motivation. In contrast to our hypothesis, students in the extrinsic goal-framing reported higher Intrinsic motivation, compared to students in the intrinsic goal-framing. For Identified regulation, results from the main effects showed that students using the mobile app, relative to textbook, reported higher Identified regulation, whereas the interaction between intrinsic goal-framing and mobile app jointly enhanced students' Identified regulation. In regard to hypothesis 2 b, the results partly supported our reasoning. For External regulation, only the main effect for identification tool was credible indicating that students using the textbook had higher External regulation compared to students using the mobile app. For Amotivation, we found one credible main effect: students in the extrinsic goal-framing, relative to intrinsic goal-framing, reported lower Amotivation.

These results were partly unexpected and in opposition to what is suggested by SDT. For instance, intrinsic goals are inwardly oriented, whereas extrinsic goals are outwardly oriented, meaning they are more associated with need-satisfaction (Vansteenkiste et al., 2010). Hence, we would expect, on average, that intrinsic goal-framing would promote autonomous regulations, whereas extrinsic goal-framing would promote controlled regulations, which was not the case. However, it is theoretically possible to pursue extrinsic goals for autonomous reasons (Ryan & Deci, 2017). That is, according to SDT, intrinsic goals are, on average, pursued for autonomous reasons due to both being associated with need-satisfaction. However, pursuing extrinsic goals because you find it important to do something (identified regulation) or because you find it interesting or enjoyable to do something (intrinsic motivation) might not be associated with negative effects (Ryan & Deci, 2017). For instance, self-integrated motives to be wealthy (i.e., financial success) might predict well-being because it may satisfy the need to feel competent and efficacious (Landry et al., 2016). Moreover, placing importance of financial success and its impact on well-being may have a differential effect across different contexts and circumstances (Frost & Frost, 2000). Hence, more research is needed to disentangle these nuances in goal-framing and its effects on motivational regulations within the mLearning field and in general.

In terms of the association between autonomous regulations on our outcome variables (H3), the results from our multi-group Bayesian path analysis partly supported our hypothesis. Specifically, we found that across both groups, the mobile app positively predicted Intrinsic motivation. Further, across both groups, Identified regulation positively predicted Intentions, and Intrinsic motivation positively enhanced Effort and Achievement. These results are in line with the theoretical propositions of SDT. That is, the positive effect of Identified regulation supports the internalization process proposed by SDT (Ryan & Deci, 2017) which suggests that understanding the value and importance of a regulation is positively related to involvement, persistence, and learning (Koestner & Losier, 2002). These results are important given that biology students report identifying sedges as uninteresting (e.g., Jeno, Grytnes, et al., 2017). The positive effect of Intrinsic motivation on Effort and Achievement has been found in numerous studies (Deci & Ryan, 2016 see for an overview), meta-analytically (Cerasoli et al., 2014), and supported by theory. For example, Ryan and Deci (2000) suggest that when intrinsically motivated, students act out of autonomy and competence. Intrinsic motivation in turn, manifests as more curiosity-based behaviour, conceptual understanding, interest, and enjoyment (Ryan & Deci, 2017), which may account for the positive effect on Achievement. An interesting finding was that for the extrinsic goal-framing group, Intrinsic motivation had a negative effect on Intentions, whereas this was not the case for the intrinsic goal-framing group. This suggests that the extrinsic goal-framing had a thwarting effect on students' intrinsic motivation for future behavioural intentions for learning about species identification. An important implication of this finding is that whereas intrinsically framing goals within identification tools didn't moderate the results between Intrinsic motivation and Intentions, extrinsically framing goals had a negative effect, which speaks to how we design and motivate behaviour within technology tools.

Finally, we found some effects that were not expected. Specifically, in the extrinsic goal-framing group, Amotivation had a positive effect on Achievement. Moreover, in the extrinsic goal-framing group, Identified regulation positively predicted Effort and Achievement, which was not the case for the intrinsic goal-framing group. These results are not in line with the theoretical assumptions of SDT that would suggest that Amotivation is negatively related to learning due to its characterization of lack of intentions, interestm and not valuing the regulation of the behaviour, and that extrinsic goals tends to be less autonomously regulated than intrinsic goals (Ryan & Deci, 2017). This could be interpreted as a paradoxical reaction to the extrinsic goal-framing. A similar positive effect of extrinsic goal-framing enhancing effort has been found by Vansteenkiste et al. (2009). However, as the authors report, the participants only "superficially memorized the material, rather than deeply process and understand it, because they would approach the material in a rigid manner." The same rigidity could be the underlying mechanism for positive effects of Identified regulation and Amotivation on effort and achievement in the external goal-framing group. More studies are needed to further evaluate these nuances of goal-framing in mLearning research, and how goal-framing is related to autonomous and controlled motivational regulations.

5.1. Limitations

There are several limitations worth mentioning when interpreting the results of the present study. First, we did not include the goal-framing within the mLearning tools which could have enhanced the internalization process of the message. We chose not to do this in order to keep the experimental manipulation similar across the experimental conditions. Specifically, it was not possible to include any message within the textbook, hence we removed this potentially confounding effect and wrote the message on paper. Future studies would need to test this hypothesis and manipulate only mLearning tools and see if intrinsic versus extrinsic goal-framing within the electronic device enhances or diminishes internalization. Second, we employed a homogenous sample of biology students in this study, hence we are not able to generalize across other subjects. It may be argued that species identification is only relevant for biologists, which then precludes the possibility to include students from other subjects. Moreover, the mLearning app is designed to support the needs for autonomy and competence within species identification. Hence, it is necessary to test these effects within this learning context. However, the general experimental design is generalizable and may be tested using other mLearning tools that support the basic psychological needs. Furthermore, the implications of goal-framing are generalizable to other contexts and mLearning designs. Third, we investigated the effects of one mLearning tool on students' Intentions, Effort, and Achievement for a short time span, which may have reduced the ability to internalize the goal-framing. For instance, our experimental design required that the students learnt the skills of species identification on the first day of a week-long field trip. Then students were presented with a goal-framing, followed by the species identification. It might be possible that the time lapse between the goal-framing and the species identification process needs to be longer. Although we found two credible interaction effects, the effects were insubstantial with a wide confidence range. Future studies would need to replicate these findings. Furthermore, the biology students used in our study might be more interested in nature and the importance of conserving it than other students. Hence, for biology students, extrinsic goal-framing might be a path to help the community or society for autonomous reasons. Biology students have also accumulated knowledge about nature, biodiversity, and species which may have a moderating role in framing different goals. Future studies would need to confirm these lines of reasoning. Fourth, External regulation showed lower psychometric values than recommended (i.e., $\alpha = \geq .70$). Given that low Cronbach's alpha reduces power in path analysis (Kline, 2011), we excluded External regulation from our model. However, we recommend interpreting the results from the other analyses with care given the lower alpha level. Last, we did not include a manipulation check to investigate whether our design successfully framed the different goals as either intrinsic or extrinsic. We did, however, include the motivational regulations which are theoretically expected to be predicted differentially by the different goal-framing. Future research should replicate our study and include a manipulation check to confirm our results.

5.2. Theoretical implications and future research

The results of the present study have multiple implications for theory and future research. It seems that extrinsic goal-framing has a different energizing effect on the participants, compared to intrinsic goal-framing, which was unexpected. More research is needed to understand whether the context of goal-framing has a differential effect on motivation, whether extrinsic goals create different processes in mLearning, or whether the experimental design should be refined and/or elaborated. Pertaining to this latter point, replicating and critically examining our experimental design is an important step towards further advancing our understanding of how different goal-framing in technology impacts students. In terms of the two credible interaction effects, more research is needed to replicate our results. Although we recommend caution in interpreting these results, our results suggest that intrinsic goal-framing in a need-supportive mobile app has a positive impact on intentions and identified regulation.

Extrinsic goals are developed through cultural practices or to the extent that the social context is need-thwarting versus need-supportive. We have argued that the mobile app is need-supportive, however, it might be that in order to promote intrinsic goals, the social context needs to be a physical agent (i.e., teacher, parent, peer) and not a technological device. Moreover, it would be useful to investigate how goal-framing in mLearning affects the needs for autonomy, competence, relatedness, and psychological well-being, since SDT suggests that basic psychological needs serve as mediators between goals and wellness (Ryan & Deci, 2017). We recommend future studies include basic psychological needs as potential mediators in mLearning research. An interesting future research avenue would be to investigate whether the interaction between goal-framing and mLearning tool affects well-being measures (e.g., affect, vitality, flourishing). This would be in line with SDT's assumption that all goals are not created equal and that the synergetic effect of intrinsic goals and need-support would positively impact well-being (Ryan & Deci, 2017). Finally, we recommend future studies employ a Bayesian approach to analyses and build statistical evidence of other studies. This would be an important step towards advancing the field both empirically and in terms of analytical strategies.

6. Conclusion

Does framing an intrinsic goal within a need-supportive mobile application enhance students' motivation, intentions, effort, and achievement for learning about biodiversity, relative to an extrinsic goal with a non-need-supportive textbook? The answer to our research question is partly yes and partly no. We found that goal-framing can impact motivation and important outcomes which is important for the mLearning community. Moreover, this could be of value for technology designers and from a theoretical perspective in order to understand the dynamics and mechanisms of how mLearning is related to important outcomes.

Author contribution

Lucas M. Jeno and John-Arvid Grytnes conceptualized and formulated the research idea; Lucas M. Jeno, Ulrich Dettweiler, and John-Arvid Grytnes developed the methodology; Lucas M. Jeno and Ulrich Dettweiler performed the analyses; Lucas M. Jeno performed original draft; Ulrich Dettweiler, and John-Arvid Grytnes performed review, editing and supervision.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compedu.2020.104022.

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