A TAGSET FOR UNIVERSITY STUDENTS' EDUCATIONAL GOALS

Felix Weber[1] and Elen Le Foll[2]
[1]*Institute of Cognitive Science*
[2]*Institute of English and American Studies*
Osnabrück University, Germany

ABSTRACT

Self-set educational goals are central to self-regulated learning and an observable manifestation of students' motivation. In this paper, we develop and trial a tagset for the characteristics of university students' self-set goals. The novelty of this approach consists in using data-driven, non-exclusive tags, rather than theory-derived, exclusive categories, on the basis of freely formulated goals in natural language. A 400-goal sample out of the 2,262 educational goals collected from 732 students at three universities was used to develop a tagset of six metatags and 28 tags. Six coders independently assigned tags to the collected goals. Based on these tag assignments (n = 376,458), Krippendorff's α was used to approximate intercoder reliability. Surprising intercoder agreement scores are discussed. Further, relative frequencies for each of the tags were calculated. These point to relevant aspects of students' motivations. The tagged dataset may serve as input for AI-powered study assistant systems, whilst the tagset itself may be used in future studies to gain further insights into university students' study motivations.

KEYWORDS

Goal Setting, Goal Characteristics, Goal Classification, Study Goals, Higher Education

1. INTRODUCTION

Goal-setting theory (Locke and Latham, 1990; Locke and Latham, 2019) postulates that by explicitly formulating personal goals individuals are more likely to attain them. Goal-setting individuals are hypothesized to be more capable of directing their effort and attention towards goal-relevant tasks and of ignoring distractions. Indeed, the setting of goals can, in itself, bolster individuals' self-regulation capacity. Furthermore, goal setting boosts persistence, thus reducing the impact of negative influences such as anxiety, disappointment or frustration. In addition, well-defined goals are thought to encourage individuals to develop more efficient strategies to meet their aims (e.g. Locke and Latham, 2002). Over the past four decades, more than 400 experimental and correlational studies have provided evidence for the validity of goal-setting theory (e.g. Locke and Latham, 2002; Latham and Locke, 2007).

Goal-setting theory is key to social-cognitive learning models of academic achievement. Within such frameworks, goal commitment and self-efficacy positively influence each other in a virtuous cycle of goal attainment (e.g. Pintrich, 2000; Morisano, 2013; Schippers *et al.*, 2015). Crucially, competences such as self-regulated learning, self-initiative, self-management and self-efficacy are all considered fundamental skills for successful studies and careers. In the context of higher education, these "future skills" are also expected to gain in importance as universities shift towards more active learning forms involving more student choices and greater learner autonomy (Ehlers, 2020, p.22). Since self-regulated learning is known to largely depend on intrinsic motivation and, crucially, the ability to set personal study goals, the ability to formulate meaningful goals is seen as a key quality for students to successfully complete their university studies.

Indeed, Locke and Latham's (1990) proposal that high but achievable goals correlate positively with performance outcomes has been shown to generalize to academic learning (cf. Morisano, 2013 for a review; also Schippers *et al.*, 2020 for a recent study). In addition, Alessandri *et al.* (2020) conclude that students' self-set goals are more likely to be attained if the goals formulated are highly specific and of moderate difficulty.

In the German context, the EU-wide Bologna reforms have introduced new challenges, particularly for Bachelor students, for whom the transition to the world of work requires an increasingly high degree of professional goal orientation and self-control (Olos *et al.*, 2014). However, a considerable proportion of students are known to be rather poor at formulating intrinsic study goals. Studies suggest that they can greatly benefit from support to both formulate and maintain commitment to self-set goals (Schippers *et al.*, 2020).

1.1 Objectives

The present paper aims to uncover and quantify the types of intrinsically motivated study goals that university students spontaneously formulate in a brief, online goal-setting exercise. To further analyze these self-set goals, a coding scheme is generated on the basis of the natural language data collected. Intercoder reliability scores and the relative frequencies of the different types of goals are calculated.

The results may inform future attempts to support students in developing and pursuing their individual study goals. Digital study assistants have the potential to support university students in self-monitoring their progress and assist them in their development, application and evaluation of strategies and behaviors for successful goal achievement (Weber, 2019). It is hoped that the successful implementation of such software may substantially improve students' learning outcomes, grades and self-efficacy.

1.2 Existing Study Goal Classifications

Two broad categories of achievement goal constructs have traditionally been contrasted. These have been alternatively termed learning and performance goals (Dweck, 1986), mastery and performance goals (e.g. Ames and Archer, 1987), or task-involvement and ego-involvement goals (Nicholls, 1984). Achievement goal theorists hypothesize that these two types of goal constructs are linked to "a divergent set of competence-relevant affect, cognition, and behavior" (Elliot, 1999, p.169). With performance (or ego-involvement) goals, students focus on their abilities and sense of self-worth, whereby ability is achieved by surpassing normative-based standards and/or the performance of others. By contrast, learning, mastery or task-involvement goals reflect the belief that effort and outcome covary. They thus highlight intrinsic motivational patterns. In contrast to performance goals, mastery goals are evaluated on the basis of self-referenced standards (Ames, 1992).

Adding to the prevailing performance-mastery goal dichotomy, Elliot (1999) added the notion of approach and avoidance and thus introduced the trichotomous framework of mastery, performance-approach, and performance-avoidance goals. In this framework, performance-approach goals focus on attaining normative competence, whilst performance-avoidance goals home in on avoiding normative incompetence. Pintrich (2000) subsequently added the, at first sight, somewhat counterintuitive construct of mastery-avoidance goals. This latter category may be associated with some forms of perfectionism; typical motivations for such goals might include *"make sure I don't make any mistakes"* or *"not get a single question wrong"* (Elliot and Thrash, 2001, p.146). At the functional level of analysis, these distinct, theoretically mutually exclusive, achievement goal categories are assumed to be associated with different outcomes, such as levels of cognitive engagement, self-regulation, affect, interest, persistence, and choice behaviors (Pintrich, 2000).

Although these goal categories have traditionally been theorized as dichotomous and in opposition to one another, empirical correlational studies based on survey data have reported conflicted results with some positive, negative and non-significant correlations between the supposedly opposing types of goals (Pintrich, 2000). A further issue with such goal classification schemes concerns the consciousness or cognitive accessibility of motivational constructs and thus whether students can accurately report on their own motivation (Murphy and Alexander, 2000). Goal-setting theory assumes that goals are cognitive representations of what individuals are trying to accomplish and their purposes or reasons for attempting a task. As such, they are inherently cognitive and assumed to be accessible by the individual. This, however, is not necessarily a given and, in real world contexts, students spontaneously formulate much more varied goals. Indeed, such self-set goals have been reported to "take on a much more personalized, idiographic flavor" (Elliot and Thrash, 2001, p.146) Furthermore, each achievement goal category potentially encompasses very many different sub-levels of goals. By way of illustration, Elliot and Thrash (2001, p.146) differentiate between high-level striving, e.g., "*learn as much as I possibly can at school this year*" and lower-level striving, e.g., "*get at least 45 out of 50 problems correct on my math exam"*. Hence the kind of goals that students freely formulate may be simple

task-based target goals, overarching goal orientations or goal complexes. In addition, goals are cognitive representations and, as such, are expected to be adapted on the basis of contextual sensibility (Pintrich, 2000).

One known issue in designing and evaluating goal-setting interventions is the difficulty of reliably classifying and coding participants' self-set goals in natural language. As a result, many studies have resorted to using study goal questionnaires designed to capture the different types of goals that students set themselves. For instance, Elliot and Church (1997) devised a questionnaire to assess college students' adoption of mastery, performance-approach, and performance-avoidance achievement goals. Participants responded to six items, such as "*It is important to me to do better than the other students"* and "*I want to learn as much as possible from this class"*, on a 7-point Likert scale ranging from "*not at all true of me"* to "*very true of me"*.

An early, data-driven attempt to classify students' self-set goals includes Krause (1995), who investigated the individual planning and decision-making processes that students go through before choosing a university course. In her analysis, students' goals were subdivided into two broad categories: subject-related goals (e.g. *pursuit of personal interests and development of personality*) and social goals (e.g. *contact with other students, communicating with lecturers*). Also in the German higher education context, Ahn *et al.* (2012) applied both previously established goals categories and added new categories on the basis of interviews and questionnaires with students and lecturers. These categories reflect goals related to the choice of a particular course of study. The authors classified them into six supra-categories. On the basis of the data collected, Ahn *et al.* (2012) proposed a four-level hierarchical model of study goals. The highest level represents the overarching aim of *living a good life*. The second level makes a temporal differentiation between goals concerning students' university studies and those concerning life after graduation. The model's third level is about the goal's contextual environment: at university vs. outside of university, and private vs. professional lives. The fourth, most fine-grained level, distinguishes between self-focus vs. other-focus, high vs. low involvement in the learning process, professional vs. personal considerations, and fulfilling personal wishes vs. those of others.

As part of a personal growth goal-setting program, Travers *et al.* (2015) explored the types of academic performance-related growth goals that students choose to set themselves. The authors subsumed these goals into three broad categories: (1) personal organization and time management; (2) emotional and psychological control; and (3) interpersonal-skills development, stressing that these need not be discrete categories. Similarly, as part of a large quasi-experimental goal-setting intervention program, Schippers *et al.* (2020) categorized students' self-set goals with a set of seven categories: academic, career, social relationships, material, physical health, mental well-being, and miscellaneous. Two independent raters classified the goals according to these seven categories and Schippers *et al.* (2020) report high interrater agreement scores of $k = 0.85–0.87$.

Prior studies on students' self-set study goals have tended to focus on one or two study disciplines (most frequently economics, management and psychology) and attempts to classify freely formulated study goals have usually been restricted to a handful of very broad goal type categories, with only few studies reporting inter-rater agreement scores. By contrast, the present study seeks to create and validate a tagset that can capture the full breadth of study goals students set themselves and that can be applied to a broad range of both under- and postgraduate studies. Ultimately, it is hoped that such a tagset, together with a large reliably manually tagged training dataset may later be used by a digital study assistant to automatically analyze students' self-set goals in order to design personalized goal-setting interventions.

2. METHODS

The procedure is summarized in Figure 1. First, students from three German universities across all study programs were invited to participate in the study using existing university- and faculty-specific email mailing lists, as well as advertising on the universities' local learning management system (LMS) platforms. As such, the sampling technique used was a combination of self-selection and convenience sampling (Oates, 2006).

The link provided in the emails and the LMS adds redirected students to a web-based interface embedded in the universities' local LMS. The webpage detailed the project's wider aims (creating a digital study assistant) and encouraged students to participate by citing research that has shown that the formulation of personal goals can, in itself, positively contribute to attaining them (Locke and Latham, 2002). Further motivation was provided by informing students that, on submission of their goals, they would be able to see the goals most frequently submitted by other students and that they would see as many as they had submitted themselves.

Thus, by submitting four goals, students would be shown the four most frequently submitted goals thus far in the study. In the first text box of the input interface (Figure 1), participants were informed of the pseudo-anonymization procedure of their personal data and could opt in to have personal information concerning their course and their current semester of study saved alongside their goals. The exact information saved was displayed next to the check box. The data collection procedure was checked by the data protection officials of the universities involved and approved to be in line with GDPR regulations. The second text box required participants to input their goals one by one. They also had the option of deleting previously submitted goals.

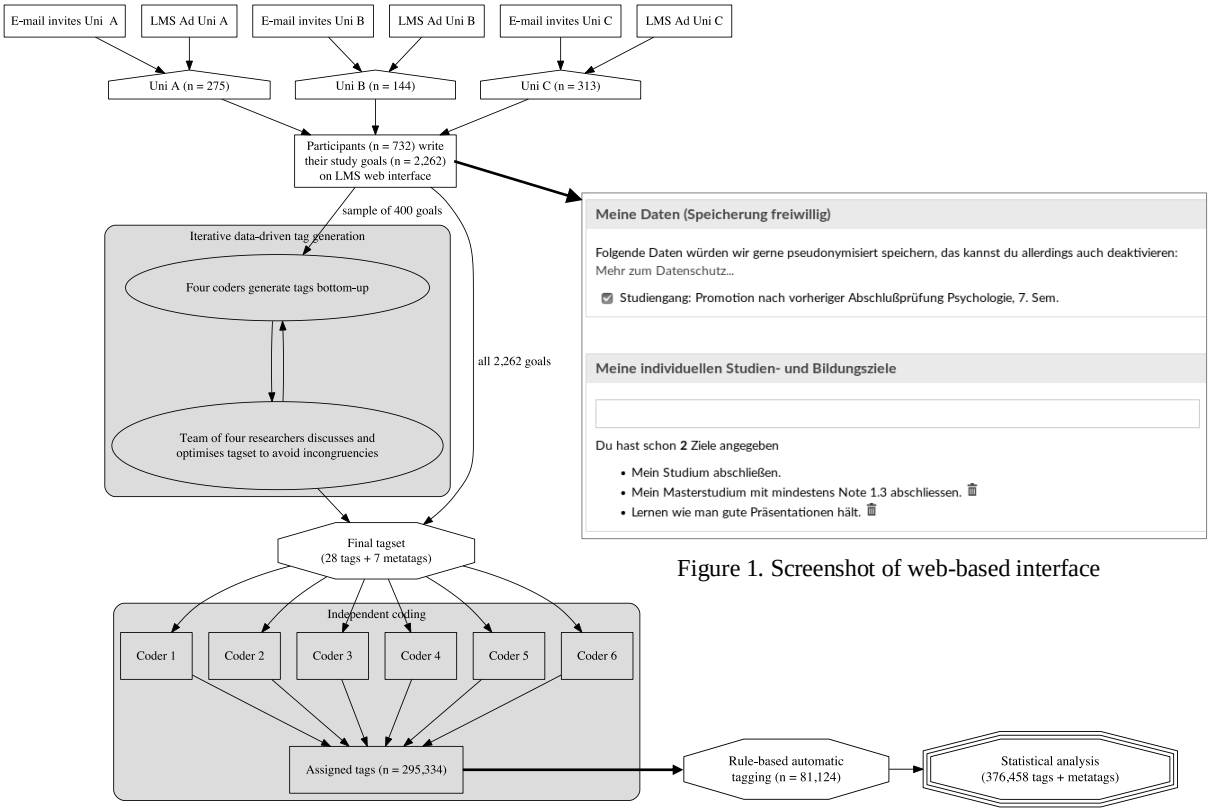

Figure 1. Screenshot of web-based interface

Figure 2. Flowchart outlining the data collection and processing procedure

Post-data collection, a random sample of 400 goals were iteratively tagged by one of the researchers following a cyclical, data-driven process, and four project members discussed and improved the proposed tags. Thus, rather than imposing preconceived categories, commonalities and key themes were identified from the data (Braun and Clarke, 2006). Six independent coders then applied the final tagset to the full set of goals collected. They were instructed to use as many of the tags for any one goal as they felt necessary.

Post-manual coding, rule-based algorithms were run to add the corresponding metatags to the goal ratings made by the six coders. For instance, if a coder assigned the tags ORIENTATION to the goal *Promotionsstelle bekommen* [get a PhD position], the metatag CAREER was automatically added. Additionally, following Bloom's (1956) taxonomy of educational objectives, the tags subsumed under the metatag *Education goals* were hypothesized to be sequentially dependent: PERSONAL GROWTH > COMPETENCES > COMPREHENSION > KNOWLEDGE. Consequently, if a goal was tagged as COMPETENCES, the tags KNOWLEDGE and COMPREHENSION were automatically added to the list of tags assigned to that goal.

Krippendorff's α (Krippendorff, 2004) was used to measure intercoder agreement. This measure was deemed most appropriate to gauge intercoder reliability since it can handle missing data and can be compared to a number of other well-known metrics (Krippendorff, 2004). Relative tag frequencies were calculated for each tag across all ratings by all raters. Data analyses were carried out in Python 3.7 using the Pandas (McKinney, 2010), NumPy (Oliphant, 2006), and Statsmodels (Seabold and Perktold, 2010) libraries.

3. RESULTS

In total, 732 students participated in the study. Among the participants, 74.69% percent agreed to provide data about their subject, degree type and semester. 2,262 goals were generated so that, on average, participants provided around 3 goals each. The length of goals varied from single words (e.g. *Abschluss* [Graduation] or *Praktika* [Work experiences]), to several elaborate sentences, e.g.:

> Ich möchte wissen wie ich realistischer Weise [sic] eine positive Auswirkung auf die Umwelt und Gesellschaft haben kann. Hochgesteckte Ziele klingen unerreichbar und niedrighesteckte [sic] Ziele klingen sinnlos. Ich möchte das Gefühl haben (und das Wissen dazu) etwas verändern zu können. [I want to know how I can realistically have a positive impact on the environment and society. Ambitious goals sound unattainable and modest goals sound pointless. I want to have the feeling (and the knowledge) to be able to change something.]

The full tagset derived from the data is listed below. As shown in Figure 3, the tags were grouped under seven metatags. This means that, for example, when a coder assigned the tag GRADES to a goal, the metatag CAREER was also automatically assigned to it.

Figure 3. Final tagset with 28 tags and seven metatags

In total, 2,262 goals were tagged. Due to time and resource constraints, the six independent coders did not all code the full dataset. A total of 295,334 manual ratings were made. Post-coding, the data cleaning process involved excluding goals identified by the coders as NON-SENSICAL utterances and NON-GENUINE goals ($\alpha = 0.712$), e.g. *Gucci Socken* [Gucci socks], and resulted in a total of 2,204 goals to be further analyzed. The results are summarized in Tables 1 and 2, which list the decreasing relative frequencies of the metatags and tags and provide an indication of intercoder reliability in the form of Krippendorff's α.

The overall very low intercoder agreement rates reveal that, in practice, many of the tags proved rather difficult to distinguish. Thus, it was originally assumed, in line with Ahn *et al.*'s (2012) hierarchical goal model, that every goal would be assigned the metatag PRIVATE OR PROFESSIONAL; in other words, that every goal would be classified as either related to (future) private, or professional life plans. In practice, however, 57.19% of goals were not be assigned this metatag. By contrast, it was not infrequent for both the PRIVATE and the CAREER tags to be assigned to the same goals. Thus, it would appear that educational goals are often tied to both personal and professional interests and that, in many cases, the two are not easily disentangled.

Conceived as a pragmatic operationalization of the concept of distal and proximal goals (Latham & Locke, 1991), the temporal scope of goals was also often hard to determine without additional background information. The α scores for the three temporal tags WITHIN THIS SEMESTER, DURING STUDIES and POST-GRADUATION are among the lowest. Theoretically, these three tags cover all the possible temporal scopes of study goals. Hence, in principle, at least one of the tags should apply to each goal formulated. However, as many as 67.14% of goals were not assigned a temporal tag. This was due, on the one hand, to participants not assigning clear temporal scopes to their goals and, on the other, to implicit temporal scopes not being inferred by the coders.

Similarly, the intercoder agreement rates reported for the EDUCATIONAL GOALS tags are also strikingly low. This is largely due to participants' often very sparse elaboration of goals. Thus, many participants formulated goals that simply read *Lernen [learn/revise]* or *Neue Inhalte erlernen [learn new things]*, for which even the four broad EDUCATIONAL GOALS tags of the present tagset (Figure 3) were already too detailed.

Table 2 shows that the tags STATUS & WEALTH and (job and financial) SECURITY (referring to job and financial security) were also frequently difficult to ascertain. Again, goals that explicitly mention these factors are rare, e.g. *Ein eigenes Haus haben [be a homeowner]*, and coders often disagreed as to when they could reasonably be inferred, e.g. *Lehrerin werden [become a teacher]* was assigned the tags STATUS & WEALTH and SECURITY by exactly half the coders.

Raters also reported that the tags NETWORKING (assigned to 46 goals) and SOCIAL CONTACT (assigned to 76 goals) were hard to distinguish from one another. The tagset included this distinction in the hope of tapping into the motives behind the two goal types. On a pragmatic level, however, coders frequently lacked contextual information to disambiguate the two so that 22 goals were assigned both the NETWORKING and SOCIAL CONTACT tags. It is worth noting that, in German culture, admitting to building relationships purely for professional reasons is often not regarded as socially acceptable and may be perceived as selfish.

Table 1. Results for metatags

Metatag Label	Krippendorff's α	Rel. freq.
PRIVATE OR PROFESSIONAL	0.409	42.81 %
CAREER GOALS	0.744	35.65 %
TEMPORAL HORIZON	0.184	32.86 %
EDUCATIONAL GOALS	0.516	32.26 %
CONCRETE GOALS	0.706	19.65 %
SOCIAL GOALS	0.685	6.43 %
α ≥ 0.800 tentative conclusive in grey, α ≥ 0.667 acceptable in light grey (Krippendorff, 2004, p. 429)		

Table 2. Results for tags

Tag Label	Krippendorff's α	Rel. freq.
PROFESSIONAL	0.525	37.85 %
KNOWLEDGE	0.516	32.26 %
DURING STUDIES	0.254	24.36 %
COMPREHENSION	0.446	20.20 %
COMPETENCES	0.533	17.39 %
GRADUATION	0.831	17.15 %
SMART (SPECIFIC, MEASURABLE, ACHIEVABLE, REALISTIC, TIME-BOUND)	0.398	12.88 %
PERSONAL GROWTH	0.477	12.74 %
JOB OPPORTUNITIES	0.612	10.73 %
POST-STUDIES	0.245	8.05 %
WORK-(RELATED) EXPERIENCES	0.697	5.24 %
GRADES	0.776	4.80 %
PRIVATE	0.262	4.66 %
GOING ABROAD	0.889	4.13 %
COMMUNICATION & CONTACT	0.716	4.06 %
FOREIGN LANGUAGES	0.903	3.90 %
TOO VAGUE	0.281	3.65 %
ACADEMIC & SCIENTIFIC SKILLS	0.582	3.60 %
FUN, HAPPINESS & SATISFACTION	0.587	3.01 %
PROGRAMMING SKILLS	0.794	2.82 %
ORIENTATION	0.487	2.68 %
STATUS & WEALTH	0.411	2.47 %
VOLUNTEER WORK & IDEALISM	0.622	1.87 %
NON-SENSICAL/NON-GENUINE GOALS	0.712	1.75 %
NETWORKING	0.664	1.48 %
DURATION OF STUDIES	0.869	0.86 %
SECURITY	0.614	0.33 %
WITHIN THIS SEMESTER	0.203	0.05 %
α ≥ 0.800 tentative conclusive in grey, α ≥ 0.667 acceptable in light grey (Krippendorff, 2004, p. 429)		

On the other hand, CONCRETE GOALS tags, such as those referring to learning a foreign language, studying abroad, graduating quickly, acquiring programming skills, obtaining good grades and gathering work experience, have a high intercoder reliability. This is probably due to their specificity and the fact that they are very frequent and, consequently, familiar to the coders, who were university students themselves.

Due to the number of students (n = 732) and, in particular, the uncontrolled variables in the selection of the participants, the external validity of the relative frequencies presented in Tables 1 and 2 towards a generalization to the goal characteristics of university students is inherently limited. Nevertheless, they reveal that the most frequent tags assigned to participants' self-set goals are CAREER, KNOWLEDGE, DURING STUDIES, COMPETENCES and GRADUATION. CAREER, here, refers to goals clearly related to either studies or work, as opposed to PRIVATE goals, hence this finding was to be expected. The fact that many of the goals were also

tagged as DURING STUDIES suggests that the majority of students' goals do refer to their current student status, as opposed to more long-term goals referring to their professional lives beyond their studies.

Indeed, many of the participants' goals revolved around learning objectives and were thus assigned the tag KNOWLEDGE. However, these goals were often highly unspecified: many simply stating *Wissen [knowledge]* or *Lernen [learning]*, courses or broad disciplines, e.g. *Biologie [biology]*, *Statistik bestehen [pass statistics]*. Other students formulated longer, but even more general goals such as *mehr Wissen sammeln, allgemein und fachspezifisch [gather more general and subject-specific knowledge]*. Nevertheless, a relatively high proportion of goals were also assigned the tag COMPETENCES, which refers to the application of comprehended knowledge. Such goals were often more specific, so that the tag COMPETENCES is highly correlated with the tags corresponding to specific skills such as PROGRAMMING and FOREIGN LANGUAGES skills, though it was also frequently assigned to goals referring to critical thinking and soft skills, for which no specific tags are included in the present tagset. Across all degree programs, many students articulated a wish to improve their foreign language skills. It is striking that such goals are also frequently formulated in a very abstract manner, e.g. *eine weitere Sprache erlernen [to a learn another language]*.

Given these examples, it will come as no surprise that the relative frequency of SMART goals is low. The intercoder agreement rate for SMART goals is also surprisingly low: this is due to a disagreement between the coders as to whether goals referring to GRADUATION, which were also among the most frequent, e.g. *Master abschließen [complete my Masters]*, should be considered specific, measurable and time-bound.

4. CONCLUSION

This study encouraged students to submit their personal study goals via an online interface embedded in universities' local LMSs. Previous research has shown that the very process of formulating such goals may induce learning and contribute to actually reaching these goals (e.g. Locke and Latham, 2002; Seijts *et al.*, 2004). In particular, Morisano *et al.*'s (2010) study concluded that detailing personal goals and strategies can significantly improve educational performance. Thus, such personal goal-setting interventions can both contribute to making the value of goals more salient, as well as help develop strategies to attain them. However, this study has made clear that, without any support, students tend to formulate very brief, unspecified goals, whereas meta-analyses have shown that specific and challenging, yet attainable goals are most likely to be reached (cf. Locke and Latham, 2002). Alternatively, Schipper *et al.* (2020) hypothesize that developing detailed strategies for goal attainment may compensate for a lack of specificity in the goal formulated. In either cases, the results of our study suggest that university students could benefit from additional support to both formulate their goals and develop specific strategies to attain them.

We suggest that a digital study assistant could provide this kind of support, at large scale, in a personalized manner. Further, such a tool could support the monitoring of goal progress, which is also known to improve effective self-regulation and increase the likelihood of successful goal outcomes (Harkin *et al.*, 2016). The present results suggest that CONCRETE goals may be most easily supported by a digital study assistant on the basis of simple rule-based algorithms. The coded data for these goals could serve as labeled training data for machine learning algorithms that can process user input in natural language. For the tags with lower α levels, more explicit rules agreed between the coders, in particular regarding information inference, may prove beneficial. Given the low intercoder agreement rates for many of these tags, this ought to be considered in future studies.

To conclude, the goal characteristics derived from the present dataset may be understood as dimensions of a multidimensional study goal space. In comparison to established categorical classification systems, which do not allow for the assignment of multiple categories to any one goal, such an approach allows for a better representation of the high complexity of goal representations.

REFERENCES

Ahn, H. *et al.* (2012) 'Entscheidungsanalytische Strukturierung fundamentaler Studienziele: Generische Zielhierarchie und Fallstudie'. *Zeitschrift für Betriebswirtschaft*, 82(11), pp. 1229–1257.

Alessandri, G. *et al.* (2020) 'Self-Set Goals Improve Academic Performance through Nonlinear Effects on Daily Study Performance'. *Learning and Individual Differences*, 77, p. 101784.

Ames, C. (1992) 'Classrooms: Goals, Structures, and Student Motivation'. *Journal of Educational Psychology*, 84(3), pp. 261–271.

Ames, C. and Archer, J. (1987) ‘Mothers’ Beliefs About the Role of Ability and Effort in School Learning’. *Journal of Educational Psychology*, 79(4), pp. 409–414.

Braun, V. and Clarke, V. (2006) ‘Using Thematic Analysis in Psychology’. *Qualitative Research in Psychology*, 3(2), pp. 77–101.

Dweck, C.S. (1986) ‘Motivational Processes Affecting Learning’. *American Psychologist*, 41(10), pp. 1040–1048.

Ehlers, U.-D. (2020) *Future Skills: Lernen der Zukunft - Hochschule der Zukunft*. Wiesbaden: Springer Fachmedien Wiesbaden DOI: 10.1007/978-3-658-29297-3.

Elliot, A. and Church, M. (1997) ‘A Hierarchical Model of Approach and Avoidance Achievement Motivation’. *Journal of Personality and Social Psychology*, 72(1), pp. 218–232.

Elliot, A.J. (1999) ‘Approach and Avoidance Motivation and Achievement Goals’. *Educational Psychologist*, 34(3), pp. 169–189.

Elliot, A.J. and Thrash, T.M. (2001) ‘Achievement Goals and the Hierarchical Model of Achievement Motivation’. *Educational Psychology Review*, pp. 139–156.

Harkin, B. *et al.* (2016) ‘Does Monitoring Goal Progress Promote Goal Attainment? A Meta-Analysis of the Experimental Evidence.’ *Psychological Bulletin*, 142(2), pp. 198–229.

Krause, G. (1995) *Lehrveranstaltungen im Studium: Herleitung und empirische Prüfung eines Modells zur individuellen Planung des Besuches von Lehrveranstaltungen*. Münster: Waxmann.

Krippendorff, K. (2004) ‘Reliability in Content Analysis’. *Human Communication Research*, 30(3), pp. 411–433.

Latham, G.P. and Locke, E.A. (2007) ‘New Developments in and Directions for Goal-Setting Research’. *European Psychologist*, 12(4), pp. 290–300.

Locke, E.A. and Latham, G.P. (1990) *A Theory of Goal Setting & Task Performance*. Englewood Cliffs: NJ: Prentice-Hall.

Locke, E.A. and Latham, G.P. (2002) ‘Building a Practically Useful Theory of Goal Setting and Task Motivation: A 35-Year Odyssey.’ *American Psychologist*, 57(9), pp. 705–717.

Locke, E.A. and Latham, G.P. (2019) ‘The Development of Goal Setting Theory: A Half Century Retrospective.’ *Motivation Science*, 5(2), pp. 93–105.

McKinney, W. (2010) ‘Data Structures for Statistical Computing in Python’. In Python in Science Conference. Austin, Texas, pp. 56–61.

Morisano, D. (2013) ‘Goal Setting in the Academic Arena’. In Locke, E.A. and Latham, G.P. (eds.) *New Developments in Goal Setting and Task Performance*. Routledge, pp. 495–506.

Morisano, D. *et al.* (2010) ‘Setting, Elaborating, and Reflecting on Personal Goals Improves Academic Performance.’ *Journal of Applied Psychology*, 95(2), pp. 255–264.

Murphy, P.K. and Alexander, P.A. (2000) ‘A Motivated Exploration of Motivation Terminology’. *Contemporary Educational Psychology*, 25(1), pp. 3–53.

Nicholls, J.G. (1984) ‘Conceptions of Ability and Achievement Motivation’. *Research on Motivation in Education*, (1), pp. 39–73.

Oates, B.J. (2006) *Researching Information Systems and Computing*. London: Sage.

Oliphant, T.E. (2006) *A Guide to NumPy*. Trelgol Publishing USA.

Olos, L., Hoff, E.-H. and Härtwig, C. (eds.) (2014) *Berufliche Zielklärung und Selbststeuerung*. Wiesbaden: Springer Fachmedien Wiesbaden.

Pintrich, P.R. (2000) ‘Multiple Goals, Multiple Pathways: The Role of Goal Orientation in Learning and Achievement’. *Journal of Educational Psychology*, 92(3), pp. 544–555.

Schippers, M.C. *et al.* (2020) ‘Writing about Personal Goals and Plans Regardless of Goal Type Boosts Academic Performance’. *Contemporary Educational Psychology*, 60, p. 101823.

Schippers, M.C., Scheepers, A.W.A. and Peterson, J.B. (2015) (1) ‘A Scalable Goal-Setting Intervention Closes Both the Gender and Ethnic Minority Achievement Gap’. *Palgrave Communications*, 1(1), pp. 1–12.

Seabold, S. and Perktold, J. (2010) ‘Statsmodels: Econometric and Statistical Modeling with Python’. In *Proceedings of the 9th Python in Science Conference*. SCIPY 2010. Austin, TX, pp. 57–61.

Seijts, G.H. *et al.* (2004) ‘Goal Setting and Goal Orientation: An Integration of Two Different yet Related Literatures’. *Academy of Management Journal*, 47(2), pp. 227–239.

Travers, C.J., Morisano, D. and Locke, E.A. (2015) ‘Self-Reflection, Growth Goals, and Academic Outcomes: A Qualitative Study’. *British Journal of Educational Psychology*, 85(2), pp. 224–241.

Weber, F. (2019) ‘Goal Trees as Structuring Element in a Digital Data-Driven Study Assistant’. In Sampson, D.G. et al. (eds.) 16th International Conference on Cognition and Exploratory Learning in Digital Age (CELDA 2019). Cagliari, Italy: IADIS Press, pp. 413–416.