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Achievement Goal Orientation Profiles and Performance in a Programming MOOC

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Tiivistelmä - Referat - Abstract

Tavoitteet. Valtaosa tietojenkäsittelytieteen kontekstissa tehdystä tavoiteorientaatiotutkimuksesta on ollut muuttujalähtöistä. Tämän tutkielman tavoitteena oli syventää ymmärrystä tietojenkäsittelytieteen opiskelijoista ja saavutusmotivaatiosta henkilösuuntautunutta lähestymistapaa käyttäen. Eri tavoiteorientaatioiden välistä vuorovaikutusta tarkasteltiin tunnistamalla yleisimmät tavoiteorientaatioprofiilit ja tutkimalla niiden välisiä eroja suoriutumisessa. Toisin kuin aiemmissa henkilösuuntautunutta lähestymistapaa hyödyntävissä tutkimuksissa, ryhmittelymuuttujina käytettiin oppimisorientaation lisäksi suoritusorientaatiota jaoteltuna tarkemmin tavoitteisiin päihittää toiset (normative goal) ja vaikuttaa pätevältä (appearance goal).

Menetelmät. Tutkimukseen osallistui 2059 avoimen internet-pohjaisen ohjelmoinnin alkeiskurssin opiskelijaa. Aineisto kerättiin kyselylomakkeella, automaattisesti arvioiduista ohjelmointitehtävistä ja loppukokeesta. Tavoiteorientaatiomittarin rakennetta tarkasteltiin eksploratiivisella faktorianalyysillä (EFA). Opiskelijat luokiteltiin ryhmiin tavoiteorientaatioiden perusteella TwoStep-klusterianalyysia käyttäen. Profiilien ominaispiirteitä ja eroja suoriutumisessa tutkittiin ristiintaulukointien ja varianssianalyysien (ANOVA) avulla.

Tulokset ja johtopäätökset. Tavoiteorientaatioprofiileja tunnistettiin viisi: Saavutusorientoituneet (31,2%), Suoritusorientoituneet (18,9%), Oppimis- ja suoritusorientoituneet (18,0%), Vähäisesti motivoituneet (17,6%) ja Oppimisorientoituneet (14,3%). Oppimis- ja suoritusorientoituneiden opiskelijoiden suoriutuminen oli kahden mittarin osalta tilastollisesti merkitsevästi parempaa kuin Vähäisesti motivoituneiden opiskelijoiden. Aiempien tutkimusten tapaan tuloksissa korostuu useampaan tavoitteeseen pyrkimisen ja suoriutumisen välinen positiivinen yhteys. Lisää tutkimusta tarvitaan tavoiteorientaatioprofiilien ja muiden koulutukseen liittyvien tulosten yhteyksien selvittämiseen ohjelmoinnin opetuksen kontekstissa. Tämänkaltaista tietoa voidaan hyödyntää uusia oppimisinterventioita ja kursseja suunniteltaessa.

Tähän tutkielmaan perustuva artikkeli ‘Achievement Goal Orientation Profiles and Performance in a Programming MOOC’ tullaan esittelemään ITiCSE 2020 -konferenssissa ja julkaisemaan konferenssijulkaisussa.

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Aims. In the context of computing education, the vast majority of prior research examining achievement goal orientations has been conducted using variable-centred methods. In order to deepen understanding of the student population and achievement motivation, this Master's Thesis employed person-oriented perspectives. The interplay of different goal orientations was explored by identifying prevalent motivational profiles and investigating profile differences in performance. Normative and appearance performance goals were handled as separate clustering variables in addition to mastery goals for the first time.

Methods. The participants were 2059 introductory programming MOOC students. Data were collected by a questionnaire and from automatically assessed programming assignments and final exam. An exploratory factor analysis (EFA) was conducted for the achievement goal orientation items to examine the factor structure. Using TwoStep cluster analysis, the students were classified into clusters according to their achievement goal orientations. Cross tabulations and analyses of variance (ANOVA) were conducted to investigate profile characteristics and differences in performance.

Results and Conclusions. Five distinct achievement goal orientation profiles were identified: Approach-Oriented (31.2%), Performance-Oriented (18.9%), Combined Mastery and Performance Goals (18.0%), Low Goals (17.6.%) and Mastery-Oriented (14.3.%). Students with Combined Mastery and Performance Goals performed significantly better than students with Low Goals regarding two metrics. Consistent with previous findings, the results highlight the positive link between multiple goal pursuit and performance. Further studies are needed to investigate motivational profiles in relation to other educational outcomes in the context of computing education. This kind of knowledge is valuable for designing interventions and new courses.

The article 'Achievement Goal Orientation Profiles and Performance in a Programming MOOC', which is based on the present thesis, will be presented at ITiCSE 2020 (Conference on Innovation and Technology in Computer Science Education) conference and published in conference proceedings.

Avainsanat - Nyckelord motivaatio, tavoiteorientaatiot, suoriutuminen, henkilösuuntautunut lähestymistapa
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Article-Based Thesis

The findings of the present thesis will be published in an article. The article, Achievement Goal Orientation Profiles and Performance in a Programming MOOC (Polso, Tuominen, Hellas & Ihantola, 2020), was composed by myself (the first author), two supervisors of this thesis and a fourth author. The article was submitted and accepted to ITiCSE 2020 (Conference on Innovation and Technology in Computer Science Education, June 2020) conference and conference proceedings. The publication is ranked as JUFO-1 in the Finnish publication forum ranking (see, https://www.julkaisufoorumi.fi/en).

As the lead author of the article, I had a substantial role in the research process. My contribution was particularly significant in chapters 2, 4 and 5, that is, Background, Results and Discussion, respectively. The final version of the manuscript was fine-tuned by all authors based on reviewers' comments.

Due to length restrictions (6+1 pages), some interesting perspectives were excluded from the paper. These perspectives, including examinations of prior programming experience and broader considerations in Introduction, Background and Discussion, are incorporated in the present thesis. The article, with the permission of the copyright holders, is provided in Appendix I.

Contents

TABLES

FIGURES

1 Introduction

Massive Open Online Courses (MOOC) have been disrupting the field of higher education for a decade now (Moe, 2015). By combining the capacity of thousands of students, high-quality instructional resources and accessibility, MOOCs open up inspirational opportunities both for institutions and individuals. Concurrently, the interest towards and demand for expertise in computer science (CS) has expanded, which sets unprecedented pressure on the field. In his recent paper, Bruce (2018) specified big challenges to be addressed in computing education. Reflecting on two of them, the potential of well-designed introductory programming MOOCs is illustrated in the following to familiarize the reader with the context of the present work. The perspective taken and key concepts of the study are presented in the last paragraph of this chapter.

The rapid increase in enrollment challenges institutions offering introductory computing education like never before. Bruce (2018) argues that MOOCs are "unlikely to have a major impact" on accelerating enrollment since they seem most beneficial for highly motivated graduates to learn specific skills. On the contrary, offering an online-based introductory programming course can reduce pressure from institutions by serving both students who consider majoring in CS but are willing to learn more before applying, and those who just need or want to learn the basics. In Finland, the introductory programming MOOC offered by University of Helsinki has attracted also high school students (Kurhila & Vihavainen, 2015) and the course has been used as an alternative path to university studies (Leinonen et al., 2019). The MOOC intake has been found to differ from the normal intake with better performance and greater retention, but unfortunately also with more pronounced gender imbalance (Leinonen et al., 2019).

On the other hand, introductory programming courses suffer from dropouts. Although not considered as "alarmingly high", the dropout rate of 33% does leave room for improvement (Bennedsen & Caspersen, 2007; Watson & Li, 2014). Interestingly, external factors (e.g., country, programming language) have not been observed to substantially moderate the effects (Watson and Li, 2014). Instead, students' internal characteristics are suggested to play a key role in determining why some of them succeed and some struggle (Watson and Li, 2014). Kinnunen and Malmi (2006) interviewed introductory programming course dropouts and discovered that the lack of time and the lack of motivation were the most prevalent reasons for dropout, and that the reasons cumulated individually, creating complex patterns. While it would be rather difficult for an educator to add more hours into the days of the busy students, motivation is more influenceable, and can be supported within MOOCs, too. Although MOOC students cannot be provided with personal scaffolding to support them when lacking motivation, they can receive automated, even customized feedback regularly (Ala-Mutka, 2005; Ihantola, 2011). Online platforms enable also fine-grained pedagogical interventions and gamification to be implemented in order to support students' motivation and prevent unnecessary dropouts (see, e.g., Hakulinen & Auvinen, 2014). In order to develop practices, research is needed to clarify the associations of different kinds of motivation and several educational outcomes. In a similar vein, Greene, Oswald and Pomerantz (2015) have suggested further research on MOOCs to take steps towards "more complex motivation constructs".

Accordingly, the present thesis contributes to the improvement of introductory programming education by investigating students' achievement motivation, namely, achievement goal orientations. Achievement goal orientations reflect individual tendencies to pursue certain types of achievement-related goals in order to attain desired outcomes (Harackiewicz, Barron & Elliot, 1998; Niemivirta, 2002; Niemivirta, Pulkka, Tapola & Tuominen, 2019). Instead of examining single achievement goal orientation dimensions, this study focuses on the patterns of goal orientations that are most prevalent amongst a sample of students attending an introductory programming MOOC. The students are clustered according to their achievement goal orientations, and the upcoming motivational profiles are compared with respect to educational outcomes, such as course performance (i.e., the person-oriented approach; see, Bergman, Magnusson, & El-Khouri, 2003; Niemivirta et al., 2019). A more comprehensive understanding of the student population is crucial for improving the largely automated course and implementing novel pedagogical interventions. Ultimately, the assignments and feedback can be customized according to individual characteristics in order to better serve a variety of students.

2 Background

Broadly, research on achievement motivation is based on two closely related concepts that are sometimes confused in the literature. Rather specific achievement-related aims are referred to as achievement goals, whereas achievement goal orientations stand for tendencies to strive for certain types of achievement goals (Niemivirta et al., 2019). While the focus of the present thesis is on the latter, studies investigating achievement goals are also reviewed, as these concepts are sometimes used rather interchangeably.

2.1 Achievement Goal Orientations and Related Outcomes

Research on achievement goal orientations started with and is still largely based on distinguishing between mastery and performance goals (e.g., Nicholls, 1984; Dweck, 1986). Mastery goals (also labelled as, e.g., task involvement) refer to an aim to develop competence, whereas performance goals (also labelled as, e.g., ego involvement) refer to an aim to outperform peers or demonstrate competence. Although this dichotomous framework is still valid and occasionally utilized in studies, further refinements in conceptualizations have taken place as the research field has expanded.

The outcomes related to the two initial goal orientations, mastery and performance, are presented in subchapter 2.1.1. The development of the theory is briefly reviewed, and some revised conceptualizations of achievement goal orientations are introduced in subchapter 2.1.2.

2.1.1 Mastery and Performance Goal Orientations

In the beginning of achievement goal orientation research, mastery goals were seen superior to performance goals due to a substantially more favorable pattern of outcomes (e.g., Dweck, 1986). Mastery goals are associated with numerous positive educational outcomes such as interest (Harackiewicz, Barron, Carter, Lehto & Elliot, 1997), adaptive learning strategies (Bouffard, Boisvert, Vezeau, & Larouche, 1995; Kaplan & Midgley, 1997; Turner, Thorpe, & Meyer, 1998), active engagement (Meece, Blumenfeld & Hoyle,

1988) and various indicators of well-being (e.g., Dykman, 1998; Daniels, Stupnisky, Pekrun, Haynes, Perry & Newall, 2009; Kaplan & Maehr, 1999).

The pattern for performance goals turns out more ambiguous. Performance goals have been linked to some positive educational outcomes such as active engagement (Meece et al., 1988), to a number of detrimental outcomes such as maladaptive learning strategies (Kaplan & Midgley, 1997) and unrelated to interest (Harackiewicz et al., 1997) and adaptive learning strategies (Bouffard et al., 1995; Kaplan & Midgley, 1997). Regarding well-being, links to both favorable (e.g., enjoyment) and unfavorable (e.g., depressive symptoms, lack of impulse control) outcomes have been reported (e.g., Dykman, 1998; Daniels et al., 2009; Kaplan & Maehr, 1999).

When it comes to academic achievement, mastery goals have been positively related (Bouffard et al., 1995; Daniels et al., 2009; Kaplan & Maehr, 1999; Roeser, Midgley, & Urdan, 1996) or unrelated (Daniels et al., 2009; Harackiewicz et al., 1997; Meece et al., 1988; Roeser et al., 1996) to desired outcomes, carrying no negative effects. Performance goals, in turn, have had positive (Bouffard et al., 1995; Daniels et al., 2009; Harackiewicz et al., 1997; Roeser et al., 1996), negative (Kaplan & Maehr, 1999; Meece et al., 1988) as well as null effects on these outcomes (Roeser et al., 1996).

2.1.2 Development of the Achievement Goal Theory

A number of explanations have emerged to clarify the underlying reasons for the rather inconsistent results. Consequently, the initial achievement goal theory with its dichotomous framework has seen many extensions over the years. Some revisions have gained support in further research while others have been more or less dismissed. In the following, some of the most essential ideas and revisions are discussed.

The multiple goals perspective was presented as a response to the confrontation between mastery and performance goals, that is to say, the presumption that solely mastery goals would promote adaptive outcomes and that only maladaptive outcomes would be linked to performance goals (i.e., the mastery goal perspective) (Harackiewicz et al., 1998). Supported by empirical findings, the multiple goals perspective acknowledges that some students do pursue more than one goal, and that both mastery and performance goals can have positive effects. Furthermore, it suggests that embracing multiple goals allows students to concurrently benefit from the various and partly differing advantages of the mastery and performance goals. (e.g., Barron & Harackiewicz, 2000; Barron & Harackiewicz, 2001; Harackiewicz et al., 1998; Pintrich, 2000.)

Other theorists found the initial framework deficient in describing achievement motivation, and the dichotomous framework was expanded trichotomous. The performance goal was partitioned into a performance-approach goal (demonstrating competence) and a performance-avoidance goal (avoiding the demonstration of incompetence) (Elliot & Harackiewicz, 1996). The former was predicted to yield null or positive effects on desirable educational outcomes whereas the latter was assumed to produce detrimental outcomes (Elliot & Church, 1997; Elliot & Harackiewicz, 1996). The framework has gained popularity and the presumed outcomes have been replicated in many studies: performance-avoidance goals are negatively associated with academic achievement (Baranik, Stanley, Bynum & Lance, 2010; Cellar et al., 2011; Hulleman, Bodmann, Schrager & Harackiewicz, 2010; Payne, Youngcourt & Beaubien, 2007; Van Yperen, Blaga & Postmes, 2014) and have several maladaptive correlates, such as low interest and feedback seeking, and high anxiety (Hulleman et al., 2010; Payne et al., 2007). On the contrary, performance-approach goals are generally either positively related (Baranik et al., 2010; Hulleman et al., 2010; Van Yperen et al., 2014) or virtually unrelated to academic achievement (Cellar et al., 2011; Payne et al., 2007). Outside of achievement, performance-approach goals are linked to both desirable and undesirable outcomes (e.g., general competence perceptions, anxiety) (Payne et al., 2007; Senko & Dawson, 2017).

Soon after introducing the performance-avoidance goal, Elliot and McGregor (2001) further proposed that the mastery goal could be distinguished likewise, forming a 2x2 achievement goal framework: the four goals would differ in terms of how competence is defined (mastery goals, performance goals) and valenced (approach goals, avoidance goals). Although some findings have provided support to their view, mastery-avoidance goals (avoiding intrapersonal incompetence, e.g., failing to learn or performing worse than before) still remain somewhat controversial (see, e.g., Bong, 2009) and are found less prevalent than the other three achievement goals (Bong, 2009; Lee & Bong, 2016;

Sideridis & Mouratidis, 2008). Mastery-avoidance goals are related to rather similar outcomes as their performance counterparts, carrying negative effects on academic achievement and interest (Baranik et al., 2010; Hulleman et al., 2010; Van Yperen et al., 2014).

The conceptualization of the performance goal (and later the performance-approach goal) has evolved over the decades of research. In the beginning of achievement goal research, demonstrating ability was seen as the essential element of the goal (e.g., Dweck, 1986; Nicholls, 1984). Later, Elliot and his colleagues defined the goal in terms of both normative success and demonstration of competence (Elliot & Church, 1997; Elliot & Harackiewicz, 1996). Eventually, Elliot and Thrash (2001) suggested that achievement motivation could be conceptualized by absolute (mastering the task), intrapersonal (improving one's skills or knowledge) and normative (outperforming others) standards of competence (i.e., the goal standard model). To demonstrate competence was not seen as a goal per se, but rather as one of the various potential reasons for goal pursuit, and the reason-goal combinations were viewed as novel motivational constructs, *goal complexes* (Elliot & Thrash, 2001; see also, Senko & Tropiano, 2016).

The multistage, still on-going process of conceptualizing and defining the performance goal has allowed a wide range of performance goal instruments to occur, resulting in varied findings and necessitating elaborate research on the nature of the goal. In order to shed light on the issue, Hulleman and his colleagues (2010) analyzed different operationalizations of achievement goals utilized in studies and their effects on academic performance. As expected, they identified two performance-approach goal components particularly widely used in scales: a normative performance goal (outperforming peers, e.g., "My goal in this class is to do better than others."; Elliot & McGregor, 2001) and an appearance performance goal (demonstrating competence, e.g., "It is important to me to validate that I am smart."; Grant & Dweck, 2003) (Hulleman et al., 2010). Springing from different ideas of success, these two types of performance-approach goals produce different effects on educational outcomes: performance-approach scales consisting of mostly normative performance goal items correlate positively with academic achievement and scales with an emphasis on appearance performance items correlate negatively with academic achievement (Hulleman et al., 2010). Moreover, normative goals tend to produce, although not completely favorable, a more adaptive set of outcomes than do appearance goals: while appearance goals are associated with self-handicapping and help-avoidance, normative goals are related to self-regulation and deep learning strategies, for example (for a review, see, Senko & Dawson, 2017). Both goals have a negative effect on help-seeking (Senko & Dawson, 2017). Interestingly, appearance goals and a goal complex of performance-approach goals pursued for controlling reasons (e.g., pleasing others or earning rewards) were found strongly correlated and related to identical, undesirable patterns of outcomes (Senko & Tropiano, 2016).

Outside the clear mastery and performance goals, also other achievement goals orientations have been identified. Outcome goals (Grant & Dweck, 2003) and extrinsic goals (initially labeled as achievement goals) (Niemivirta, 2002) refer to an aim to succeed or do well in particular tasks. Further, mastery-extrinsic goals refer to the goal of developing competence combined with a tendency to assess the level of task mastery with extrinsic criteria (e.g., grades and formal feedback) (see, e.g., Tuominen-Soini, Salmela-Aro & Niemivirta, 2008). Work-avoidance goals, in turn, differ from other strivings fundamentally by reflecting the goal of putting forth as little effort as possible (e.g., Nicholls, Patashnick, & Nolen, 1985).

2.2 Achievement Goal Orientations in Computing Education

In the context of computing education, the role of achievement goal orientations has been studied recently in various settings.

Zingaro and his colleagues investigated the effects of achievement goals in introductory computing courses within three studies (Zingaro, 2015; Zingaro & Porter, 2016; Zingaro et al., 2018). Mastery goals appeared favorable: in the first two studies, and at all six institutions investigated in the third study, mastery goals were positively related to post-course interest in CS. Regarding exam grades, both positive and null effects were observed. (Zingaro, 2015; Zingaro & Porter, 2016; Zingaro et al., 2018.) The pattern for performance goals was more complex. In the first study, performance goals were unrelated to interest and negatively related to exam grade (Zingaro, 2015). When operationalized as normative and appearance performance goals in the second and third studies, both components were mainly unrelated to interest and exam grade. However, a negative link between appearance goals and interest was discovered in the second study and an unexpected positive (albeit barely significant) correlation between normative goals and exam grade at one institution in the third study (Zingaro & Porter, 2016; Zingaro et al., 2018). Additionally, Zingaro and Porter (2016) found that adopting either normative or appearance goals was adaptive in terms of exam grade while striving for both or neither of the goals was maladaptive. Zingaro and his colleagues (2018), in turn, discovered that either high or low scores in both goals were almost equally beneficial for exam grade at one of the six institutions. The reasons for pursuing normative goals (i.e., goal complexes) were taken into account in the third study. Autonomous strivings appeared beneficial especially with respect to interest, whereas the effects for controlling strivings were null. (Zingaro et al., 2018.)

The research field comprises a variety of studies conducted in online learning environments. Hao and his colleagues (2017) studied the associations of achievement goals and different forms of online help seeking. Only marginal correlations were observed (Hao, Barnes, Wright & Branch, 2017). Some studies examined the relations between achievement goals and pedagogical interventions, namely, achievement badges and visualizations of learning behavior (Auvinen, Hakulinen & Malmi, 2015; Hakulinen & Auvinen, 2014; Ilves, Leinonen & Hellas, 2018). An interest towards achievement badges was related to performance approach and mastery extrinsic goals, whereas an interest towards heatmap visualizations was related to performance avoidance goals (Auvinen et al., 2015). Relative to completed exercise points, students with strong performance approach goals and students with strong mastery goals seemed to benefit from a radar visualization significantly more than from a textual visualization. Furthermore, even the control group without any visualizations performed significantly better than the group with textual visualizations, when the students emphasized performance approach goals (Ilves et al., 2018).

2.3 Achievement Goal Orientation Profiles

The present study brings a new, person-oriented perspective into the discussion on achievement motivation in the context of introductory programming education. While variable-oriented approaches are used to study the relations between a set of variables, person-oriented approaches shed light into the actual occurrence of certain phenomenon among the sample at hand (Bergman et al., 2003). Based on clustering the individuals according to their achievement goal orientations, the person-oriented approach enables the comparison of the upcoming motivational profiles in relation to personal features and academic outcomes, such as gender and course performance. Each profile represents individuals that are motivationally similar to each other but differ from the rest of the sample. (Niemivirta et al., 2019; see also Bergman et al., 2003.)

Comprehensive bodies of research implemented using the person-oriented approach have been summarized in two recent reviews. Wormington and Linnenbrink-Garcia (2017) relabeled the profiles identified in 23 independent samples based on their raw mean scores to facilitate systematic comparison between different profile types. Niemivirta and his colleagues (2019) reviewed 71 studies and compared the profiles according to their originally given labels. Niemivirta and his colleagues (2019) observed that the most common number of extracted profiles has been four, both among the reviewed studies regardless of educational level and among the studies investigating students in higher education and adult studies. The types of the extracted profiles depend, naturally, partly on the complexity of the achievement goal orientation framework in use and the measures conducted. However, there are certain profiles that tend to occur across studies and some general inferences have been drawn about their related outcomes.

According to both reviews, a predominantly mastery goal profile and a combined mastery and performance-approach goal profile have been the most common across studies and also the most adaptive with respect to educational outcomes. A predominantly mastery goal profile is particularly beneficial for motivation and well-being (Niemivirta et al., 2019; Wormington and Linnenbrink-Garcia, 2017), and students holding combined mastery and performance goals seem to thrive in their studies most consistently (Niemivirta et al., 2019). A profile type with average levels of all goals appeared also common in both reviews, whereas only Niemivirta et al. (2019) found predominantly performance goal and low goals profiles prevalent. While performance-oriented students tend to exhibit moderate achievement and well-being, profiles with average levels of goals are linked to moderate or relatively poor educational outcomes (Niemivirta et al., 2019; Wormington and Linnenbrink-Garcia, 2017). Profiles characterized by low goals are related to maladaptive outcomes (Niemivirta et al., 2019).

To my knowledge, no prior research has investigated both normative performance and appearance performance goal orientations using the person-oriented approach. Some studies, however, share two important premises with the present one: a simple achievement goal orientation framework (only mastery and performance goals) and the context of higher education. In such studies, the following profiles were identified: a predominantly mastery, a predominantly performance, a multiple goals (i.e., high mastery/high performance) and a low motivation profile (i.e., low mastery/low performance) (Bouffard et al., 1995; Daniels et al., 2008; Dela Rosa & Bernardo, 2013; Dull, Schleifer & McMillan, 2015; Koul, Clariana, Jitgarun & Songsriwittaya, 2009; for summary, see Niemivirta et al., 2019). With respect to academic achievement, the results were coherent across the studies: amotivated students performed significantly lower than students with other motivational profiles (Bouffard et al., 1995; Daniels et al., 2013; Dela Rosa & Bernardo, 2013; Dull et al., 2015). Additionally, students holding multiple goals and mastery-oriented students performed significantly better than performance-oriented students in two studies (Bouffard et al., 1995; Dela Rosa & Bernardo, 2013).

In the context of computing education, there is at least one prior study in which the person-oriented approach has been utilized in order to identify achievement goal orientation profiles. In their work, Hakulinen and Auvinen (2014) examined the effects of gamification on an online CS course. They identified four profiles: success (high overall mastery and performance goal orientations, low work avoidance goal orientation), mastery, indifferent and avoidance. There were statistically significant differences between the profiles in points earned during the first half of the course and course grade, indicating that success-oriented students displayed the highest performance (Hakulinen & Auvinen, 2014).

3 Aims and Hypotheses

3.1 Aims

The aim of this thesis was to investigate the motivation of introductory programming MOOC students by identifying achievement goal orientation profiles and examining profile differences in course performance.

Constant improvements and innovative interventions are required in order to address the various challenges posed on computing education (see, e.g., Bruce, 2018). This process can be facilitated by offering educators accurate, research-based knowledge of psychological phenomena affecting students' behavior, for example, achievement goal orientations as in the present study. Although some prior studies have investigated achievement motivation in the context of computing education (e.g., Hao et al., 2017; Zingaro et al., 2018), the examinations have been limited to variable correlations and regressions, and a focus on individual motivational patterns has been scant (see, however, Hakulinen & Auvinen, 2014).

Generally, research on achievement goal orientation profiles has expanded in the past two decades and studies have been conducted using various conceptualizations of achievement goals (see, Niemivirta et al., 2019). However, there are no prior person-oriented studies explicitly including the distinction into normative and appearance performance goals. These two goals are proven to have distinct outcomes (Hulleman et al., 2010), but are seldom studied together since some of the most frequently utilized achievement goal frameworks define and operationalize the essence of performance-approach goals emphasizing either normative success (e.g., AGQ, Elliot & McGregor, 2001) or appearing competent (e.g., PALS Revised, Midgley et al., 2000), or mix both conceptualizations without separation (e.g., PALS, Midgley et al., 1998). To address this gap, the present study examines both normative performance and appearance performance goal orientations alongside mastery.

Hence, this thesis adds understanding about the student population which can be used to improve online introductory programming education, and broadens knowledge of achievement goals, their occurrence and related academic outcomes.

Accordingly, the objective of the present study was to investigate:

1. What kinds of achievement goal orientation profiles can be identified among the programming MOOC students?
2. How do students with different achievement goal orientation profiles differ with respect to course performance?

3.2 Hypotheses

Based on previous findings in the context of higher education, I expected at least a predominantly mastery goal profile and a combined mastery and performance goals profile to occur (Niemivirta et al., 2019; Wormington and Linnenbrink-Garcia, 2017). A predominantly performance goal profile and a low goals profile were also anticipated likely to emerge, as in previous studies with similar achievement goal orientation framework (Bouffard et al., 1995; Daniels et al., 2008; Dela Rosa & Bernardo, 2013; Dull et al., 2015; Koul et al., 2009, for a review, see, Niemivirta et al., 2019).

Regarding course performance, I expected students with the combined mastery and performance goals profile to exhibit highest performance (Niemivirta et al., 2019) and students with the low goals profile to perform relatively poorly (Bouffard et al., 1995; Daniels et al., 2013; Dela Rosa & Bernardo, 2013; Dull et al., 2015; for a review, see, Niemivirta et al., 2019).

4 Methods

4.1 Context and Participants

The study was conducted within an open online introductory programming course offered by the University of Helsinki during Spring 2019 (see, https://ohjelmointi-19.mooc.fi/). Since the course was an open online course, it was taken by both affiliated and non-affiliated students. The overall workload of the course was 5 ECTS (European Credit Transfer and Accumulation System), which translates to approximately 135 hours of study. The course covered the basics of programming and consisted of small assignments for practicing particular constructs as well as larger assignments in which several constructs were combined. In total, there were more than 240 programming assignments in the course divided over seven parts. Each part had a set deadline. The course was evaluated based on course assignments (50% of the overall grade) and an end-of-course-exam (50% of the overall grade). The assignments were automatically assessed, and both the assignments and the exam could be completed at a distance.

The participants were 2059 students (M_{age} = 35 years; 41.4% female) taking the introductory programming MOOC described above, who completed a survey assessing achievement goal orientations and a set of background variables. The online survey was administered at the beginning of the second week of the course. Participation in the study was voluntary. Participation rate was 57.5%.

4.2 Measures

The instrument used for assessing students' achievement goal orientations combined scales from PALS (Midgley et al., 2000) and AGQ-R (Elliot & Murayama, 2008) (see, Zingaro & Porter, 2016). Measures of achievement goals included mastery goals (3 items, e.g., "My goal is to learn as much as possible."), normative performance goals (3 items, e.g., "My aim is to perform well relative to other students."), and appearance performance goals (5 items, e.g., "One of my goals is to look smart in comparison to other students in my class."). Students rated all items on a seven-point scale ranging from 1 ("not true at all") to 7 ("completely true"). The questionnaire was translated into Finnish, using the same translation as Zingaro et al. (2018).

In addition, the students were asked to report their year of birth, gender, and prior programming experience in hours in order to characterize the student population. The birth year values were converted into age values. The age values of students younger than 18 years and those few with a self-reported birth year before the 20th century were handled as missing data, as well as the gender values of students who reported 'Other'.

Lastly, four metrics were used to measure students' performance in the course: 1) the points from programming assignments (equals to the number of correctly completed assignments), 2) the number of active weeks (when students were able to complete at least one assignment), 3) participation in the final exam, and 4) course grade. Regarding the course grade metric, the students who participated the exam but did not pass were given a course grade of 0, and students who did not participate the exam were handled as missing data.

4.3 Analyses

First, an exploratory factor analysis (EFA) with an oblique rotation (Direct Oblimin) was conducted for the achievement goal orientations using Maximum Likelihood extraction to examine factor structure. Accordingly, composite scores were computed for the three achievement goal orientations, and their internal consistencies were evaluated by calculating Cronbach's alpha values. Self-reported programming experience in hours was converted into two variables. The precise programming experience variable contained reported hours as such, and non-numerical responses were handled as missing data. For the rough programming experience variable, the students were categorized either as novices (0 hours of programming experience) or non-novices (more than 0 hours of programming experience). The correlations between all variables were examined. TwoStep cluster analysis was used to classify the students into homogenous groups according to their achievement goal orientations. Cluster characteristics regarding the background variables and differences in performance were investigated using chi-square cross tabulations and analyses of variance (ANOVA). Analyses were conducted using SPSS 25.

5 Results

5.1 Preliminary Results

Exploratory factor analysis for the achievement goal items indicated a three-factor solution, which accounted for approximately 73% of the variance. All items loaded for the three factors as expected, as shown in Table 1, and the factors were labeled accordingly. Appearance performance goals, normative performance goals and mastery goals had eigenvalues of 4.648, 2.870 and 1.342, respectively. Appearance goals explained 39%, normative goals 23% and mastery goals 11% of the variance.

The internal consistencies of the achievement goal orientation mean variables are presented in Table 2. Descriptive statistics for and correlations between all variables are also shown in Table 2. Normative performance goals had a significant positive correlation with mastery goals and appearance performance goals, but mastery goals and performance appearance goals were unrelated. All three achievement goals correlated positively with the programming points and active weeks performance metrics but were not linked to course grade (see Table 2).

Table 1. Factor Loadings of the Achievement Goal Orientation Items.

	factor 1	factor 2	factor 3	(h^2)
Performance, appearance				
I aim to look smart compared to others in my class.	.92			.83
One of my goals is to show others that class work is easy for me.	.88			.75
One of my goals is to look smart in comparison to other students in my class.	.87			.77
One of my goals is to have other students in my class think I am good at my class work.	.83			.70
One of my goals is to show others that I'm good at my class work.	.74			.58
Performance, normative				
I am striving to do well compared to other students.		.96		.89
My goal is to perform better than the other students.		.87		.79
My aim is to perform well relative to other students.		.84		.72
Mastery				
I am striving to understand the content of this course as thoroughly as possible			.88	.75
My aim is to completely master the material presented in this class.			.83	.72
My goal is to learn as much as possible.			.77	.60
Eigenvalues	4.648	2.870	1.342	
Variance explained %	39.162	23.247	11.040	
Cumulative variance explained	39.162	62.410	73.450	

Note. Loadings with absolute values below 0.3 are omitted from the table.

Table 2. Descriptive Statistics, Correlations, and Internal Consistencies.

Measures	1.	2.	3.	4.	5.	6.	7.	8.
1. Mastery	-							
2. Normative	.34**	-						
3. Appearance	-.02	.36**	-					
4. Age	-.05*	-.16**	-.11**	-				
5. Experience	.01	.02	.00	.16**	-			
6. Points	.06**	.08**	.06**	-.05*	.10**	-		
7. Weeks	.05*	.07**	.07**	-.04*	.09**	.98**	-	
8. Grade	.05	.02	.02	-.07	.03	.33**	.04	-
M	5.89	4.37	2.23	35.26	526.02	138.27	4.24	4.13
SD	0.97	1.61	1.30	11.97	3284.98	94.20	2.54	1.59
Cronbach's alpha	.862	.921	.924					

Note. Experience = prior programming experience, Points = Points from the programming assignments, Weeks = number of actice weeks.
*p < .05, **p < .01

5.2 Achievement Goal Orientation Profiles

5.2.1 Identified Profiles

A TwoStep cluster analysis was carried out resulting in a five-cluster solution. Silhouette score .4 indicated a fair fit of the model. The identified profiles were labeled as Approach-Oriented, Performance-Oriented, Combined Mastery and Performance Goals, Low Goals and Mastery-Oriented. The achievement goal orientation profiles are visualized in Figure 1 (mean scores) and Figure 2 (standardized scores). Profile differences in clustering variables (i.e., achievement goal orientations) are presented in Table 3. As shown in Figure 1, mean scores in mastery goal orientation were relatively high across the profiles and mean scores in appearance performance goal orientation were rather low.

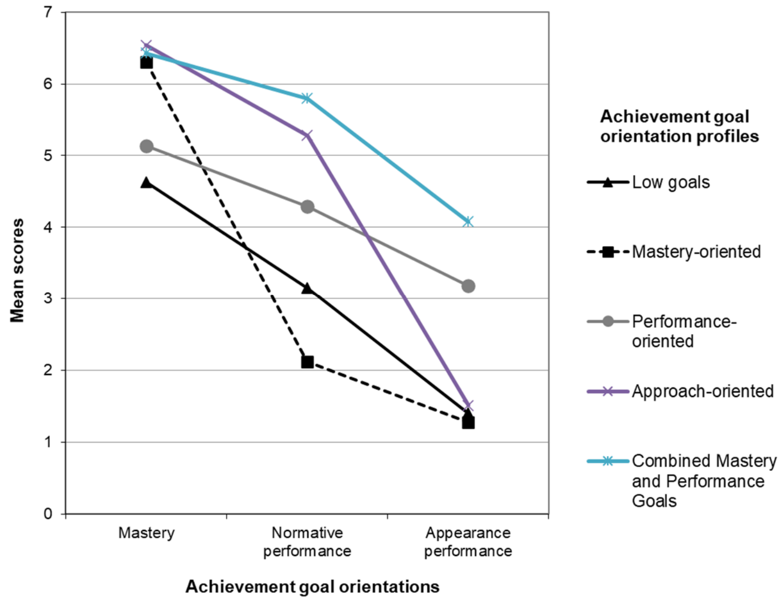

Figure 1. Students' Raw Mean Scores on Achievement Goal Orientations.

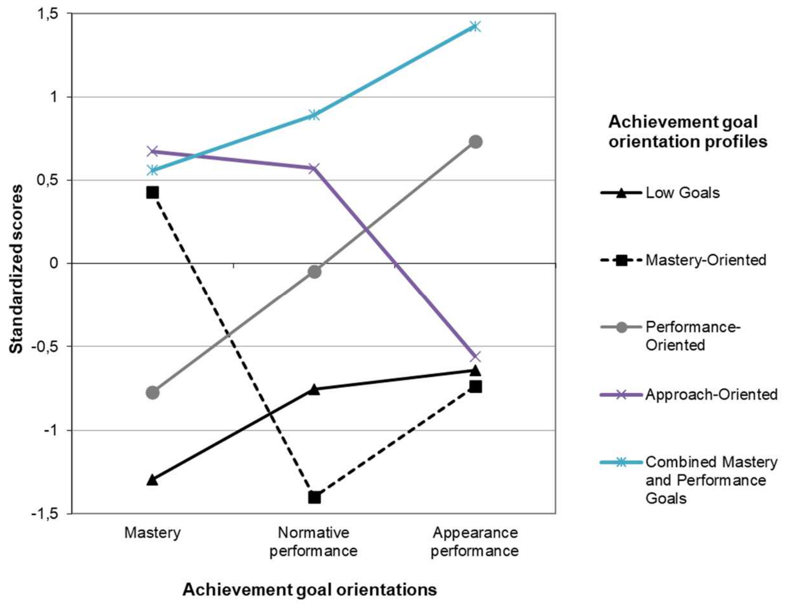

Figure 2. Students' Standardized Mean Scores on Achievement Goal Orientations.

Table 3. Mean Differences in Achievement Goal Orientations between the Profiles.

	Approach-O. N = 643		Performance- N = 389		Combined G. N = 370		Low G. N = 363		Mastery-O. N = 294				
Variable	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	F(4,2054)	p	η^2
Mastery	6.54	0.46	5.13	0.73	6.43	0.52	4.63	0.71	6.30	0.51	894.710	< .001	.64
Normative	5.28	1.07	4.29	0.94	5.80	0.90	3.15	1.08	2.12	0.84	848.371	< .001	.62
Appearance	1.51	0.53	3.18	0.83	4.08	0.99	1.40	0.50	1.28	0.44	1315.407	< .001	.72

Note. All group means are significantly different at p < 0.05 level (with Games-Howell correction).

The largest cluster, Approach-Oriented[1], consisted of almost a third of the students (*N* = 643, 31.2%). The profile was characterized by high mastery and normative performance orientations, while appearance performance orientation was low. Thus, Approach-Oriented students strove to master the content and perform well compared to other students.

Performance-Oriented students (*N* = 389, 18.9%) had relatively high scores on appearance performance orientation and average scores on normative performance orientation. On the contrary, scores on mastery orientation were relatively low, which is exceptional in the present dataset. Performance-Oriented students sought normative success and appearing proficient.

Nearly a fifth of the students embraced all three measured achievement goal orientations. This cluster was labeled Combined Mastery and Performance Goals (*N* = 370, 18.0%). Relative to other profiles, this profile was characterized by remarkably high mean score in appearance orientation. Students with Combined Mastery and Performance Goals were motivated in several ways: they attempted to master the content but also aimed at performing better and appearing more knowledgeable than other students.

Students with Low Goals (*N* = 363, 17.6%) expressed relatively low levels of all three achievement goal orientations. Mastery and normative performance orientations were particularly low considering the sample average.

Mastery-Oriented students (*N* = 294, 14.3%) formed the smallest cluster in the present sample. While highly motivated by mastery, these students displayed the lowest levels of both performance orientations. Mastery-Oriented students strove to learn and master the course content but were not motivated by any normative comparisons or show offs.

5.2.2 Profile Differences in Background Variables

While all profile differences were significant and effect sizes were between medium and large in terms of the clustering variables (i.e. achievement goal orientations) (see Table

[1] According to the goal standard model (Elliot & Thrash, 2001), performance-approach goals refer to an aim to outperform others, and appearance goals per se do not represent performance-approach motivation. The group of students holding both mastery (i.e., mastery-approach) and normative performance (i.e., performance-approach) goals was therefore labeled Approach-Oriented (see also, Jansen in de Wal et al., 2016).

3), only minimal significant differences were traced in relation to the background variables: age, gender and programming experience (see Tables 4 and 5).

A one-way ANOVA was carried out to investigate the links between age and achievement goal orientation profile. Significant differences were found, $F(4,2040) = 8.35$, $p < .001$, $\eta^2 = .02$. Post-hoc comparisons using the Bonferroni correction indicated that differences between the oldest two clusters and the youngest two clusters were significant. Mastery-Oriented students ($M = 37.33$, $SD = 12.62$) and students with Low Goals ($M = 37.27$, $SD = 11.27$) were oldest, whereas students with Combined Mastery and Performance Goals ($M = 33.09$, $SD = 12.79$) and Approach-Oriented students ($M = 34.59$, $SD = 11.39$) were youngest.

A chi-square test of independence showed a significant association between gender and achievement goal orientation profile, χ^2 (4) = 13.63, $p = .009$, $C = .08$. Females were overrepresented (std. res. = 2.1) in the Low Goals cluster, and even though the threshold of -2 was not exceeded, it seems that males were slightly underrepresented (std. res. = -1.8) in the Low goals cluster.

Examined with a one-way ANOVA, no significant relations were found between the precise programming experience and achievement goal orientation profile, $F(4,1943) = .13$, $p = .970$, $\eta^2 = .00$. However, a comparison of the proportions of novices and non-novices with a chi-square test of independence yielded a significant result, χ^2 (4) = 16.18, $p < .005$, $C = .09$. Novices were overrepresented (std. res. = 2.1) in the Low goals cluster.

Table 4. Cross-Tabulation of Background Variables and Profiles.

	Gender		Programming experience	
	Male	Female	Novice	Non-novice
Approach-Oriented	372 (58.4%)	265 (41.6%)	229 (36.6%)	396 (63.4%)
Performance-Oriente	239 (62.9%)	141 (37.1%)	111 (29.3%)	268 (70.7%)
Combined Goals	227 (62.9%)	134 (37.1%)	112 (31.3%)	246 (68.7%)
Low Goals	180 (51.3%)	**171 (48.7%)**	**141 (40.3%)**	209 (59.7%)
Mastery-Oriented	164 (57.1%)	123 (42.9%)	84 (29.1%)	205 (70.9%)

Note. Bold values denote overrepresentation.

5.3 Profile Differences in Course Performance

The associations between the five achievement goal orientation profiles and performance outcomes were studied using four metrics: (1) total points from the weekly assignments, (2) total weeks during which the student was active, (3) attendance in exam, and (4) course grade. Profile differences in performance metrics are presented in Tables 6 and 7.

Profiles differed significantly with respect to the number of points gained from assignments, $F(4,2054) = 2.94$, $p = .019$, $\eta^2 = .01$. Post-hoc comparisons using the Bonferroni correction indicated that the mean score for the Combined Mastery and Performance profile ($M = 149.03$, $SD = 93.43$) was significantly higher than the mean score for the Low Goals profile ($M = 126.87$, $SD = 93.00$). Moreover, a chi-square test of independence showed that students who correctly completed all programming assignments were underrepresented (std. res. = -3.0) in the Low goals cluster, $\chi^2(4) = 18.65$, $p = .001$, $C = .10$.

Results for the active weeks metric were also significant, $F(4,2054) = 2.62$, $p = .033$, $\eta^2 = .01$, and congruent with those for the programming assignment points. Post-hoc comparisons using the Bonferroni correction indicated that the mean score for the Combined Mastery and Performance profile ($M = 4.51$, $SD = 2.49$) was significantly different from the mean score for the Low Goals profile ($M = 3.98$, $SD = 2.57$). However, students who participated during all weeks of the course were equally distributed in the profiles, $\chi^2(4) = 4.76$, $p = .313$, $C = .05$.

Profile differences in exam attendance were non-significant, $\chi^2(4) = 6.75$, $p = .150$, $C = .06$, and so were differences in passing the exam, $\chi^2(4) = 7.76$, $p = .101$, $C = .06$. Finally, achievement goal orientation profile did not significantly predict course grade, which consisted of programming points (50%) and exam grade (50%), $F(4,561) = 1.50$, $p = .202$, $\eta^2 = .01$.

Table 5. Mean Differences in Background Variables between the Profiles.

	Approach-O.			Performance-O.			Combined G.			Low G.			Mastery-O.							
Variable	*N*	*M*	*SD*	*N*	*M*	*SD*	*N*	*M*	*SD*	*N*	*M*	*SD*	*N*	*M*	*SD*	*df*	N	*F*	*p*	η²
Age	641	34.59ac	11.39	386	35.36	11.7	363	33.09bd	12.79	361	37.27ab	11.27	294	37.33cd	12.62	4	2040	8.346	< .001	.02
Experience	610	504	3040	366	520	3097	347	547	3136	345	468	3505	280	651	4105	4	1943	0.134	= .970	.00

Note. Group means sharing the same superscripts are significantly different at p < 0.05 level (with Bonferroni correction).

Table 6. Cross-Tabulation of Course Performance Metrics and Profiles.

	Completed all assignments		Participated all weeks		Participated exam		Passed grade	
	False	True	False	True	False	True	False	True
Approach-Oriented	490 (76.2%)	153 (23.8%)	386 (60.0%)	257 (40.0%)	461 (71.7%)	182 (28.3%)	482 (75.0%)	161 (25.0%)
Performance-Oriente	314 (80.7%)	75 (19.3%)	228 (58.6%)	161 (41.4%)	278 (71.5%)	111 (28.5%)	289 (74.3%)	100 (25.7%)
Combined Goals	280 (75.7%)	90 (24.3%)	211 (57.0%)	159 (43.0%)	258 (69.7%)	112 (30.3%)	270 (73.0%)	100 (27.0%)
Low Goals	314 (86.5%)	**49 (13.5%)**	232 (63.9%)	131 (36.1%)	282 (77.7%)	81 (22.3%)	294 (81.0%)	69 (19.0%)
Mastery-Oriented	234 (79.6%)	60 (20.4%)	184 (62.6%)	110 (37.4%)	214 (72.8%)	80 (27.2%)	219 (74.5%)	75 (25.5%)

Note. Bold values denote underrepresentation.

Table 7. Mean Differences in Course Performance between the Profiles.

	Approach-O.		Performance-O.		Combined G.		Low G.		Mastery-O.						
Variable	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*df*	N	*F*	*p*	η²
Points	139.18	94.91	141.46	93.35	149.03a	93.43	126.87a	93.00	132.49	95.64	4	2054	2.944	= .019	.01
Weeks	4.24	2.54	4.36	2.54	4.51a	2.49	3.98a	2.57	4.06	2.54	4	2054	2.624	= .033	.01
Grade	4.10	1.65	4.14	1.53	4.25	1.55	3.88	1.75	4.45	1.27	4	561	1.496	= .202	.01

Note. Group means sharing the same superscripts are significantly different at p < 0.05 level (with Bonferroni correction).

6 Discussion

The aim of the present study was, firstly, to investigate the achievement goal orientation profiles on an introductory programming MOOC and, secondly, to study profile differences in course performance. Mastery, normative performance, and appearance performance goal orientations were measured. The study had two interesting and novel premises: the normative and appearance dimensions of the performance goal were studied employing a person-oriented approach for the first time, and on the other hand, there are only few prior studies on achievement goal orientations that were conducted in the computing education context using a person-oriented approach.

6.1 Motivational Profiles

The findings regarding the identified achievement goal orientation profiles were mostly in line with prior research. Five profiles were extracted and, as hypothesized, the commonly identified profiles emerged: a mastery-oriented profile, a combined mastery and performance goals profile, a performance-oriented profile, and a low goals profile (see, Niemivirta et al., 2019; Wormington and Linnenbrink-Garcia, 2017). Some profiles (i.e., performance-oriented and combined mastery and performance goals), however, were characterized with novel features as students displayed high appearance performance goals alongside the typical pattern.

Around a fifth of the students embraced all three achievement goals. This cluster was labeled Combined Mastery and Performance Goals. Students who, in turn, had relatively low motivation with respect to all goals, formed the Low Goals cluster. Other clusters consisted of students who shared a similar motivational pattern with an emphasis on one or two of the goal orientations. The largest of all clusters was Approach-Oriented (31%). Approach-Oriented students were motivated by mastery goals and normative comparisons but did not emphasize appearing competent. Performance-Oriented students aimed at normative success and appearing talented. Finally, the smallest cluster, Mastery-Oriented (14%), was characterized by high mastery goals and the lowest normative and appearance performance goals of all profiles. It should be noted that mean scores in mastery orientation were relatively high across all of the profiles and mean scores in appearance performance orientation were rather low.

6.2 Goal Orientation and Course Performance

Students in the Combined Mastery and Performance Goals group stayed active on the course for longest and gained most points from the programming assignments, performing significantly better than students holding Low Goals who dropped out earliest and gained less programming assignment points. Differences in performance between other profiles were non-significant. Although the effect sizes were small, the findings turned out as anticipated and hypothesized. Across studies, a combined mastery and performance goal profile seems to serve as an adaptive motivational pattern in terms of academic achievement for students in upper secondary school and higher education (e.g., Bouffard et al., 1995; Tuominen-Soini et al., 2011). It has been proposed that this effect is due to the challenging and performance-focused educational contexts (Tuominen-Soini et al., 2011). On the contrary, students with a low motivation have shown the weakest performance also in prior studies (e.g., Daniels et al., 2013; Dela Rosa & Bernardo, 2013; Dull et al., 2015).

6.2.1 Contextual Factors, Goal Pursuit and Course Performance

Some students' achievement motivation and thereby performance may have been affected by the course format. Firstly, Senko, Hama and Belmonte (2013) discovered that mastery goals were related to an interest-based study strategy, which in turn was related to low exam grades in mostly closed-format exams. Performance goals, by contrast, were related to a vigilant study strategy, which was related to high exam grades as long as their teachers were relatively clear about how to succeed (Senko, Hulleman & Harackiewicz, 2011). Although a minority of students in the present sample took the actual final exam, the course was built on rather closed, automatically assessed online assignments, seemingly aiding the vigilant performance-oriented students. On the other hand, no evidence was found that more open-ended exercises would indirectly support mastery-oriented students' exam performance through their interest-based study strategy (Senko et al., 2013).

Further, in the context of programming, smaller tasks are proven beneficial for learning the basics of a topic and also seem to reduce the likelihood of postponing subsequent, more complex exercises (Denny, Luxton-Reilly, Craig & Petersen, 2018). There is no reason to believe that more open-ended assignments would support students to learn more or perform better in introductory programming. Additional studies, however, are needed to test this hypothesis.

Secondly, the effects of MOOC, a completely distance learning, online-based course format, on students holding different achievement goal orientation profiles is yet to be studied. Mastery-approach goals have been included in some studies on MOOC students (e.g., de Barba, Kennedy & Ainley, 2015; Wang & Baker, 2015), but to my knowledge there are no studies investigating how the online learning environment affects goal pursuit. For example, the essence of performance normative goals is outperforming peers, and not having the chance to compare presumably impacts the strongly normatively-striven students' motivation somehow. Are these students at risk of becoming amotivated? Is there a chance to guide them to reorient towards other goals, and if so, by what means? There is evidence that instructional practices can influence how students' goal orientations change over time: an emphasis on relative ability made students more preoccupied with performance goals whereas students in task-focused learning environments exhibited fewer negative shifts (Anderman, Maehr & Midgley, 1999). Interventions enhancing interest and relevance, and practices focused on temporal progress rather than normative comparisons are seen beneficial for all students (e.g., Butler, 2006; Tuominen, 2011; see also, Urdan & Midgley, 2003), especially those not strongly embracing any goal particularly (Tuominen, Niemivirta, Lonka & Salmela-Aro, 2020). Further research is needed to explore mastery-focused interventions in online learning environments and their effects on performance-oriented students.

6.2.2 Novices and Students with Low Goals

Replicating the findings of previous studies, prior programming experience was positively related to course performance (e.g., Zingaro et al., 2018; Zingaro & Porter, 2016), but unrelated to the three achievement goals (Zingaro & Porter, 2016). Regarding the motivational profiles, novices were overrepresented among the students holding Low

Goals. Whether the novices (and other students with low goals) found it unrealistic to pursue any of the achievement goals, or just curiously registered to a potentially interesting course without strong intentions to thoroughly master the basics of programming or outperform others, their course performance turned out poorest of all students. These students clearly need particular attention and scaffolding, but it is doubtful whether interventions that intend to nurture and boost inner motivation also work for students without much of it. Hakulinen and Auvinen (2014) have suggested that while low performing students might not be interested in additional challenge, they could benefit from constant encouraging, such as being rewarded even for small achievements.

6.2.3 Other Outcomes Related to Goal Pursuit

Alongside prior programming experience, a range of factors related to students' background and personality can influence course performance but were beyond the scope of this work. On the other hand, goal pursuit is proven to be associated with other outcomes alongside academic achievement. In the present study, students in the Combined Mastery and Performance Goals group appeared highest performing, but other outcomes were not measured. There is evidence that as well as the performance-oriented students, and even more so, students with combined mastery and performance goals are prone to emotional distress (e.g., stress, emotional exhaustion) (Tuominen-Soini et al., 2008). Achievement motivation is also known to be linked with post-course interest in the subject. In the context of computing education, interest is strongly related to mastery goals and mostly unrelated to performance goals (Zingaro, 2015; Zingaro & Porter, 2016; Zingaro et al., 2018). Taking into account these aspects is of relevance when assessing what kinds of motivational profiles offer the most favorable premises for both academic success and other important outcomes, and how adopting these tendencies could be supported.

6.3 Perspectives on Performance Goals

The definition and effects of performance goals have been debated for long. While identifying reliable arguments, it is important to pay attention to the different conceptualizations and operalizations of these goals, and the impact of other associated factors. Although some of the discussed effects cannot be verified with the data at hand, they offer relevant lenses through which to view the results.

6.3.1 Appearance Goals

Previous studies have shown appearance goals negatively related or unrelated to educational outcomes (for a review, see Hulleman et al., 2010), the latter also in CS context (Zingaro & Porter, 2016; Zingaro et al., 2018). Contrary to expectations, the present results show a significant positive - yet weak - relation between appearance goals and two performance metrics: points from programming assignments and active weeks. In the present study, Combined Mastery and Performance Goals and Approach-Oriented profiles were distinguished solely by the level of appearance goals, whereas mastery and normative goals went pretty much hand in hand. Moreover, as it turned out, Combined Mastery and Performance Goals profile with its relatively high level of appearance goal, was the most advantageous profile in terms of academic achievement. Approach-Oriented profile, with a considerably lower level of appearance goal, did not differ from other profiles significantly.

Appearance and normative performance goals had not been studied using a person-oriented approach before now, but examining the interactions of these two goals had resulted in puzzling findings: in one study, striving for one of them was adaptive and for both or neither was maladaptive (Zingaro & Porter, 2016), but subsequent results suggested that having either high or low scores in both were almost equally beneficial (Zingaro et al., 2018). Still another kind of conclusion can be justified based on present findings, as it seems that the interaction of the three goal orientations is positively related to academic achievement, and that appearance goals do not hinder, but boost this effect. It is clear that additional studies are needed to further investigate these interactions.

6.3.2 Normative Goals

Brophy (2005) has brought into discussion a critical perspective on the assumed causality between performance-approach goals and academic achievement. It is mostly the already well-performing students who find these goals realistic and rate them high, he argues, as the performance-approach items often emphasize normative performance in a rather absolute manner (e.g., “My goal is to perform better than most (or all) of the other students”). Also empirical findings link perceived competence with performance-approach goals (Elliot & Church, 1997). The performance normative items in this study were somewhat more open to interpretation (e.g., “My goal is to perform better than the other students”). There was no correlation between prior programming experience and normative goals, and measures of students’ perceived competence, study skills and habits, prior academic success and other attributes of high achievers were not included. Therefore, no conclusions can be drawn concerning the background of students with high normative performance goals.

In the goal standard model presented by Elliot & Thrash (2001), the definition of achievement motivation is based on three standards of competence: absolute, interpersonal, and intrapersonal. Aims outside these three standards are not seen as achievement goals at all. Following the logic, only the normative goal of the present study counts as an actual performance-approach goal. However, the strive for demonstrating ability is not dismissed either, but is seen as one of the multiple reasons individuals may have for their normative goal pursuit, alongside with autonomous reasons (e.g., enjoyment or challenge-seeking), for example (see, Senko & Tropiano, 2016). Acknowledging the unique conceptualizations and relations of the normative and appearance performance goals and also the incoherence of the performance goal research, Senko and Tropiano (2016) conclude by stating that goal complexes could have what it will take to “coalesce the field over the long run”.

6.4 Implications for Practice

The findings of this thesis can be utilized to facilitate the improvement of online introductory programming education. Although students across all profiles already endorsed relatively high mastery goals, they might benefit from further support to endorse mastery, learning, and understanding. Mastery-approach goals are seldom, if ever, linked to any harmful effects on either performance or well-being, and also performance goals seem to carry the most positive effects when coupled with mastery (Niemivirta et al., 2019; Wormington & Linnenbrink-Garcia, 2017). As stated by Luxton-Reilly and his colleagues (2018), a wide range of educational approaches, activities and interventions have been reported to affect introductory programming students positively. Some students, especially the already high performing ones, seem to benefit from achievement badges and visualizations (Auvinen et al., 2015; Hakulinen & Auvinen, 2014; Ilves et al., 2018), which indeed reflect personal progress and mastery. Additionally, to attract mastery goals, students could be provided with ideas how to utilize and further practice the elementary programming skills already acquired, and inspiring sneak peeks of what is to be learned in the following sections of the course. Further research is needed to establish the effects of such interventions on students with different achievement goal orientation profiles.

6.5 Limitations and Future Research

This study comes with a set of limitations, which will be addressed next. The study was conducted in one specific country and in the context of one specific programming course, which naturally affects the generalizability of the results. Only the students who completed a voluntary questionnaire in the beginning of the course and agreed to provide research consent were included in the sample - about 60% of the students did. It is therefore unclear how representative the motivational profiles and their proportional sizes are. Since one of the major aims of the present study was obtaining a deeper understanding of the student population, these aspects must be taken into account when interpreting the findings and making inferences from them.

The background data and achievement goal orientations were collected utilizing a self-report questionnaire, which might have caused some students to intentionally or unintentionally respond untruthfully. This, however, is unlikely to affect the overall results as the sample was rather large. Prior programming experience was asked to be reported in hours. The numeral responses ranged from zero to tens of thousands. Some participants did not report programming experience numerically, and many of these responses were untranslatable into hours (e.g., 'five years', 'countless'). Two variables were computed: for the precise programming experience variable, the non-numerical responses were handled as missing data; for the rough programming experience variable, many non-numerical responses could be interpreted as more than 0 hours of programming experience and these students were categorized as non-novices. Due to the subjective nature of the estimated programming experience in hours, the division between novices and non-novices, although not as precise, was likely to characterize the student population more reliably.

Students' achievement goal orientations were measured using a framework that consisted of mastery, normative performance, and appearance performance goal items. This framework has been utilized before, also with the same Finnish translation (Zingaro et al., 2018). While intentionally focusing on the distinction between normative and appearance performance goals, the framework ignores some goal orientations, such as performance-avoidance and work avoidance goals. Thus, the extracted profiles may not capture all main dimensions of students' achievement motivation.

Apart from achievement goal orientations, many other individual tendencies and contextual factors also affect educational outcomes. While there was data of students' prior programming experience, other important aspects, such as access to help, could not be controlled for. As both the assignments and the final exam were conducted at-distance, some students might have utilized their own networks and resources to foster learning and course performance, while others may have not had access to such help. On the other hand, broadening the perspective from mere short-term academic success would be of importance, as motivational profiles are proven to differ also with respect to other outcomes such as students' satisfaction with their subsequent educational choices and many indicators of well-being (Tuominen et al., 2011; Tuominen-Soini, Salmela-Aro & Niemivirta, 2012). Challenging enough, a post-course survey would be needed to examine these important outcomes. Given that only about 60% of the students completed the first survey, the post-course survey would be likely to generate even more biased data of the whole student population.

There are also several strengths in the present thesis. Centrally, the large sample, a total of 2059 participants, allowed all analyses to be performed reliably. While the study focused on person-oriented methods, some variable-oriented analyses were also conducted. These examinations partly replicated those of two prior studies (Zingaro & Porter, 2016; Zingaro et al., 2018), generating comparable data of the student populations. Several course performance metrics were in use, of which all were based on automatically computed points from and temporal data of the programming assignments and exam rather than self-reports.

To summarize, future research on goal orientation profiles should use more comprehensive performance goal frameworks to further refine what is known about these goals. Since related to unique patterns of outcomes, including at least normative and appearance goals as well as performance-avoidance goals would be of relevance. Acknowledging the conceptual disagreements concerning the appearance performance goal, research on goal complexes could also be a solution (Elliot & Thrash, 2001). There is evidence that appearance performance goals and performance-approach goals pursued for controlling reasons are highly correlated and share a similar pattern of outcomes (Senko & Tropiano, 2016). More studies, however, are needed to establish this interesting finding. Additionally, while the present study focused solely on academic achievement, it is important that attention is paid to several educational outcomes when assessing the advantages and disadvantages related to each motivational profile. Yet, as far as I know, no such studies have been carried out in the context of programming education and MOOCs. In a more practical level, different types of assignments, interventions focused on mastery (e.g., challenges, gamification, visualizations) and other educational experiments should be incorporated into future courses and study their effects on students with different motivational profiles.

7 Conclusions

The purpose of the present study was to investigate introductory programming MOOC students' achievement motivation by examining their achievement goal orientation profiles in relation to course performance. Normative and appearance performance goals were employed as clustering variables alongside mastery goals, which had never been done before.

Considering the first research question, what kinds of achievement goal orientation profiles can be identified among the programming MOOC students, five distinct profiles were extracted: Approach-Oriented, Performance-Oriented, Combined Mastery and Performance Goals, Low Goals and Mastery-Oriented. While the profiles are characterized by somewhat typical patterns of achievement motivation, they are unique due to the uncommon set of clustering variables. According to the present findings, the differentiation of normative and appearance performance goals seems meaningful.

Regarding the second research question, how do students with different achievement goal orientation profiles differ with respect to course performance, findings were in line with previous research indicating that students with Combined Mastery and Performance Goals perform significantly better than those holding Low Goals. No other differences in course performance were observed between the five profiles. Taking another perspective from prior studies, striving for both mastery and performance goals on a high level has also been associated with less adaptive outcomes, such as stress and burnout. The complexity of achievement motivation students exhibit and the various outcomes of goal pursuit necessitate elaborate research on these phenomena. In the context of computing education, there is much scope for additional studies on students' individual motivational tendencies, also in relation to pedagogical interventions. Such research is valuable for improving introductory programming education, both online and on campus, to meet the needs of curious experimentalists as well as future experts.

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Appendix I: Manuscript

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Achievement Goal Orientation Profiles and Performance in a Programming MOOC

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ABSTRACT

It has been suggested that performance goals focused on appearing talented (appearance goals) and those focused on outperforming others (normative goals) have different consequences, for example, regarding performance. Accordingly, applying this distinction into appearance and normative goals alongside mastery goals, this study explores what kinds of achievement goal orientation profiles are identified among over 2000 students participating in an introductory programming MOOC. Using Two-Step cluster analysis, five distinct motivational profiles are identified. Course performance and demographics of students with different goal orientation profiles are mostly similar. Students with Combined Mastery and Performance Goals perform slightly better than students with Low Goals. The observations are largely in line with previous studies conducted in different contexts. The differentiation of appearance and normative performance goals seemed to yield meaningful motivational profiles, but further studies are needed to establish their relevance and investigate whether this information can be used to improve teaching.

CCS CONCEPTS

• **Applied computing → E-learning**.

KEYWORDS

Achievement Goal Orientation, Performance, CS1, MOOC

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1 INTRODUCTION

Motivation is the key force that drives students to seek new knowledge and learn [25, 27]. Motivational strivings are multiple and whereas some students may have goals related to high grades, outperforming others or appearing competent, others may strive for intrinsic objectives such as mastering the topic at hand. Achievement goal orientation is one of the most prominent constructs used to study these achievement-related motivational factors in various learning and achievement settings. Achievement goal orientations describe students' tendency to prefer certain types of goals and outcomes over some others in achievement-related settings [24].

Achievement goal orientations are typically divided between mastery and performance goals (e.g., [6, 23]). Mastery goals refer to an aim to develop competence, whereas performance goals refer to an aim to outperform peers or demonstrate competence. While these two types of goals still remain as the core and basis for a variety of achievement goal frameworks, the modern view on motivational factors has expanded this dichotomous scheme and includes further refinements.

Methodologically achievement goal orientation research can be divided between variable- and person-oriented approaches. While variable-oriented approach focuses on the relations between achievement goal orientation variables (i.e., dimensions of achievement goal orientations) and learning-related outcomes (e.g., performance, interest, or well-being), person-oriented approach [3] focuses on combinations of variables and extracts groups of students who display similar combinations of achievement goal orientations.

Most of the previous applications of achievement goal orientation theory in computing education research rely on the variable-oriented approach (e.g., [40–42]), with only few studies exploring achievement goal orientation profiles. However, for example, Hakulinen and Auvinen [13] have applied the person-oriented approach to identify student profiles in an online data-structures and algorithms course, and used this information to understand how achievement-badges suit different student profiles.

In this study, we adopted the same achievement goal orientation framework Zingaro et al. [41] have used in the context of introductory programming education. In contrast to these previous studies, we used the person-oriented approach and, first, explored what kinds of achievement goal orientation profiles can be identified among students participating in a programming MOOC (**RQ1**) and, second, investigated whether students with different achievement goal orientation profiles differ with respect to their course performance (**RQ2**). Improved understanding of the student population (i.e., what patterns of achievement goal orientations students show and how big a proportion of students show a particular pattern) may have implications on planning of teaching and learning.

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2 BACKGROUND

2.1 Achievement Goal Orientation Dimensions

The dichotomous (i.e., mastery vs. performance) achievement goal framework has seen many extensions over the years, the distinction between performance-approach (demonstrating competence) and performance-avoidance goals (avoiding the demonstration of incompetence) [7, 8] being probably one of the widest spread of them. Mastery-avoidance goals (i.e., avoiding misunderstanding or failing to learn) came along soon after (2 × 2 framework [9]). Both performance-avoidance and mastery-avoidance goals have been proven maladaptive in terms of performance [2, 16] and are also related to a range of other negative effects, such as fear of failure, low self-determination [9] and low help seeking behavior [2].

Hulleman, Senko et al. [16, 29, 31] have further suggested that there is a need to distinguish between performance goals focused on appearing talented (appearance goals) and those focused on outperforming others (normative goals). Springing from different ideas of success, these two types of performance goals are related to different outcomes: performance-approach scales consisting of mostly normative goal items correlated positively with achievement and scales with an emphasis on appearance goal items correlated negatively with achievement.

2.2 Profiles and Academic Achievement

There is already a large number of studies utilizing a person-oriented approach and examining students' achievement goal orientation profiles in various educational contexts (e.g., K12, and higher education). Although the number and nature of the identified profiles in each study naturally depend partly on, for example, the achievement goal measures used and the sample characteristics, some generalizations can still be drawn. It seems that the number of identified goal profiles has varied mainly between three and six with slightly fewer profiles (most commonly three) often identified among younger (e.g., elementary school) students and somewhat more profiles found among older (e.g., university) students (see Niemivirta et al. [24]). Moreover, certain profiles tend to occur across studies. Most common profiles seem to be a predominantly mastery goal profile, a predominantly performance goal profile, and a combined mastery and performance goal profile as well as profiles with moderate and low levels of achievement goals.

There has been debate in achievement goal literature over the benefits of endorsing mastery goals versus combined mastery and performance goals [32]. The empirical findings have been threefold in demonstrating that the mastery-oriented students have the highest academic achievement (e.g. [11]), that students holding both mastery and performance-approach goals display the highest academic achievement (e.g. [34]), or that these two groups perform equally well (e.g. [4, 26]). In addition, it has been shown that predominantly performance goal profile has been linked with moderate achievement, whereas average and low goal profiles with relatively poor academic achievement (e.g. [4, 34]). Variation in these results have also been related to the contextual differences, for example, by stating that mastery goals may be harmful if the tasks (e.g., graded assignments) are closed rather than open-ended [30]. This is especially interesting as automatically assessed programming assignments are often closed by their very nature [12]. Nevertheless, it is important to note that some studies have not found notable differences in performance or academic achievement between goal orientation profiles (e.g. [28]).

2.3 Achievement Goal Orientations in Computing Education

In the context of learning programming, Zingaro et. al have studied achievement goals in relation to performance, enjoyment and post-course interest in three subsequent studies [40–42]. The first study from 2015 focused on mastery and performance goals (without the normative vs. appearance separation) [40]. Findings of this study indicate that while mastery goals are related to good exam performance (r=.19), performance goals may have negative consequences (r=-.3). The follow up study from 2016 [42] introduced the normative and appearance separation and was not able to replicate any of the previous correlations between (normative or appearance) performance goals, mastery goals and exam performance. In multiple regression model, however, mastery goals were still significant and related to increased exam performance. While normative and appearance performance goals were not significant, their interaction was. This examination of the interactions is an interesting step towards person-oriented approach. Finally, replication study from 2018 involved six institutions in four countries [41]. Results varied between institutions, indicating importance of the context.

Interestingly, the interaction of the two performance-approach goal components appeared to result in opposite performance outcomes [exam grade] depending on the study. The earlier study [42] found that adopting only normative or appearance goals was adaptive while striving for both or neither of the goals was maladaptive. The later follow up study, in turn, found that in one of the six institutions either high or low scores in both goals were almost equally beneficial [41].

The research on achievement goal orientations in computing education comprises also studies conducted in other contexts. For example, visualizations of learning behavior and achievement badges have had a different impact on students depending on their achievement goals [1, 13, 18]. In addition, students with different achievement goals were observed to have little or no differences in terms of online help seeking [14].

In the context of an online CS course, Hakulinen and Auvinen [13] investigated students' achievement goal orientations using a person-oriented approach and identified four profiles: success (high all except for avoidance), mastery, indifferent, and avoidance.

3 METHODS

3.1 Context

The study was conducted within an open online programming course offered by the University of Helsinki during Spring 2019. The course is taught using Java and covers the basics of programming, ranging from handling standard input and output to the basics of object-oriented programming and algorithmics. The course uses an online textbook with theory, videos, program visualizations, programming assignments, and quizzes. Programming assignments are worked on within an IDE and students' work is automatically assessed using an automated assessment system that provides scaffolding and informative feedback on students' progress [37].

The course is divided into seven parts and it uses a teaching approach previously described e.g. in [36]. While most of the programming assignments in the course consist of a single small task intended for practicing a particular construct, many of the assignments scaffold students in constructing larger programs through the use of multiple tasks as a part of the problem descriptions. In total, the course has over 240 programming tasks divided over the seven parts. Each part has a set deadline, and the students are expected to complete at least 25% of the assignments in each part in order to be able to proceed to the subsequent part. If a student does not complete the minimum required assignments, they cannot continue in the course. Instead, they are offered an option to move to a course with no deadlines, giving them the opportunity to study at their own pace.

The overall workload of the course is 5 ECTS (European Credit Transfer System), which translates to approximately 135 hours of study. While the course is an open online course, it is taken by both affiliated and non-affiliated students. For affiliated students, the course counts towards degree requirements, while the non-affiliated students may receive credits of the course at their own institution, may use the course as a training for a job, or may use the course simply for the purposes of learning something new.

The course is graded based on completed programming assignments and an end-of-course exam. As the course is given online, both the exam and the assignments can be completed at a distance using a computer. The grade of the course is formed based on course assignments (50% of overall grade) and the exam (50% of the overall grade). The highest mark can be attained by collecting at least 90% of the available course points, while the minimum passing rate is 50% of the total available course points. Regardless of the grading, the student must receive at least half of the exam points to be eligible for a course grade and the course credits.

3.2 Participants and Measures

The participants were 2059 students (M_{age} = 35 years; 41.4% female) participating in an introductory programming MOOC, who completed a questionnaire assessing achievement goal orientations. The online questionnaire was administered in Spring 2019 at the beginning of the second week of the course described above. Furthermore, data from students' course assignments and exam performance were collected. Participation in the study was voluntary. Participation rate was 57.5%.

The instrument by Zingaro and Porter [42] was used for assessing students' mastery goals (3 items, e.g., "My goal is to learn as much as possible."), normative performance goals (3 items, e.g., "My aim is to perform well relative to other students."), and appearance performance goals (5 items, e.g., "One of my goals is to look smart in comparison to other students in my class."). Students rated all items on a seven-point scale ranging from 1 ("not true at all") to 7 ("completely true"). The questionnaire was translated to Finnish, which is the language used in the studied context. The Finnish translation was the same as in [41]. In addition to the achievement goal orientation survey, self reported age, and gender were used to characterize the student population.

Students' performance was measured by using 1) the points from automatically assessed programming assignments (equals to the number of correctly completed assignments), 2) the number of active weeks (when students were able to complete at least one assignment), 3) participation to the final exam, and 4) final course grade.

3.3 Data Analyses

Confirmatory factor analysis was used to validate the goal orientation questionnaire. Composite scores were computed for each of the three achievement goal orientations, and their internal consistency was evaluated by calculating their Cronbach's alpha values. Also, the correlations between all variables were examined. TwoStep cluster analysis was used to classify students into homogeneous groups according to their scores on the achievement goal orientation scales. Configural frequency analyses (CONFA) were conducted for examining how females and males, students who participated or did not participate during all weeks of the course, students who participated or did not participate in the final exam, and students who passed or did not pass the final exam were distributed in the groups. CONFA [38] compares the observed to expected frequencies in a cross-tabulation and asks whether cell frequencies are larger or smaller than could be expected based on some chance model. Types are patterns that are observed more frequently than expected by chance and antitypes are patterns that are observed less frequently than expected by chance. Furthermore, analyses of variance (ANOVA) were performed to investigate group differences in course performance. Analyses were conducted using Mplus and SPSS 25.

4 RESULTS

4.1 Preliminary Results

Factor analysis of the achievement goal items indicated that the assumed three-factor model fit the data well, χ^2 (41, N = 2120) = 315.36, p < 0.001, CFI = .984, RMSEA = .057, SRMR = .033. Error covariances between one pair of similarly worded items were freed. Descriptive statistics, Cronbach's alpha reliabilities, and correlations for all continuous variables are presented in Table 1.

4.2 RQ1: Achievement Goal Orientation Profiles

A TwoStep cluster analysis resulted in a five-cluster solution. Silhouette score .4 indicates a fair fit of the model. The achievement goal orientation profiles are visualized in Figure 1.

The profiles were labeled as Approach-Oriented[1] (N=643, 31.2%), Performance-Oriented (N=389, 18.9%), Combined Mastery and Performance Goals, N=370, 18.0%), Low Goals (N=363, 17.6%), and Mastery-Oriented (N=294, 14.3%). The differences between profiles in clustering variables were all significant, as illustrated in Table 2.

Application of CONFA (χ^2 (4, N=2016)=13.63, p=0.009) revealed that it was typical for female students to be in the Low Goals group (type) and untypical for male students to be in this group (antitype).

[1]The label is inspired by work of Senko [29], arguing that, according to the goal standards model, the 'real' performance-approach goal is the striving to outperform others (i.e., normative) and it is also the one that produces more positive effects with respect to, for example, academic achievement, compared to appearance performance goals. As approach-oriented students scored high in both mastery (i.e., mastery-approach) and normative performance (i.e., performance-approach) goals, the label approach-oriented was chosen for this group (see also [19]).

Table 1: Correlations between continuous variables, their means (M), standard deviations (SD), and Cronbach's alpha (α) for latent variables. Significance levels are reported after Holm's correction for multiple comparisons, *p<.05, **p<.01, and ***p<.001

	1.	2.	3.	4.	5.	6.	M	SD	α
1. Mastery							5.98	0.97	0.86
2. Normative perf.	0.34***						4.37	1.61	0.92
3. Appearance perf.	-0.02	0.36***					2.23	1.30	0.92
4. Points	0.06*	0.08**	0.07*				138.3	94.3	-
5. Weeks	0.05	0.07*	0.07*	0.98***			4.24	2.54	-
6. Grade	0.05	0.06*	0.05	0.62***	0.60***		1.14	2.03	-
7. Age	-0.05	-0.16***	-0.10***	-0.06	-0.05	-0.06*	35.3	12.0	-

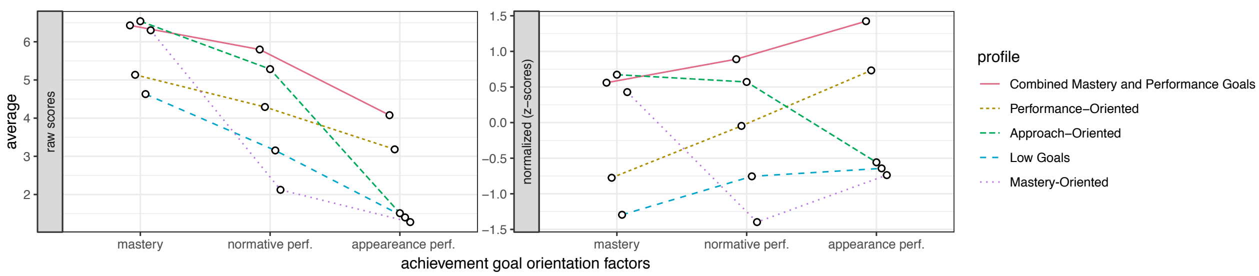

Figure 1: Achievement goal orientations (mean values) for all profiles.

Table 2: Mean values, standard deviations and one way ANOVA of achievement goal orientation dimensions between all profiles. Combined stands for the Combined Mastery and Performance Goals profile.

	Approach-Oriented		Performance-Oriented		Combined		Low Goals		Mastery-Oriented				
	M	SD	M	SD	M	SD	M	SD	M	SD	F(4,2054)	p	η^2
Mastery	6.54	0.46	5.13	0.73	6.43	0.52	4.63	0.71	6.30	0.51	894.710	< .001	.64
Normative perf.	5.28	1.07	4.29	0.94	5.80	0.90	3.15	1.08	2.12	0.84	848.371	< .001	.62
Appearance perf.	1.51	0.53	3.18	0.83	4.08	0.99	1.40	0.50	1.28	0.44	1315.407	< .001	.72

Table 3: Cross-tabulation of binary performance metrics (i.e., studying till the last week, participating exam, and getting a passed grade from the course) and achievement goal orientation profiles.

	Participated all weeks		Participated exam		Passed grade		
	FALSE	TRUE	FALSE	TRUE	FALSE	TRUE	n
Combined Mastery and Performance Goals	211 (57%)	159 (43%)	258 (69.7%)	112 (30.3%)	270 (73%)	100 (27%)	370
Performance-Oriented	228 (58.6%)	161 (41.4%)	278 (71.5%)	111 (28.5%)	289 (74.3%)	100 (25.7%)	389
Approach-Oriented	386 (60%)	257 (40%)	461 (71.7%)	182 (28.3%)	482 (75%)	161 (25%)	643
Low Goals	232 (63.9%)	131 (36.1%)	282 (77.7%)	81 (22.3%)	294 (81%)	69 (19%)	363
Mastery-Oriented	184 (62.6%)	110 (37.4%)	214 (72.8%)	80 (27.2%)	219 (74.5%)	75 (25.5%)	294

4.3 RQ2: Profile Differences in Performance

When investigating performance on a high level, CONFAs revealed equal distribution of students in the achievement goal orientation groups regarding those students who participated during all weeks of the course and those who did not (χ^2 (4, N=2059)=4.76, p=0.313), those who participated in the final exam and those who did not (χ^2 (4, N=2059)=6.75, p=0.150), and those who passed the final exam and those who did not (χ^2 (4, N=2059)=7.76, p=0.101). Distributions of these measures are provided in Table 3.

In more detailed analysis, profiles differed significantly with respect to programming assignment points, F(4,2054)=2.94, p=.019, η^2=.01. Post-hoc comparisons using the Bonferroni correction indicated that the mean score for the Combined Mastery and Performance Goals profile (M=149.03, SD=93.43) was significantly different than for the Low Goals profile (M=126.87, SD=93.00). There were no other significant differences between the profiles for this metric.

Table 4: **Mean values, standard deviations and one way ANOVA of performance measures between all profiles. Combined stands for the Combined Mastery and Performance-Oriented profile.**

	Approach-Oriented		Performance-Oriented		Combined		Low Goals		Mastery-Oriented				
	M	SD	M	SD	M	SD	M	SD	M	SD	F(4,2054)	p	η^2
Points	139.18	94.91	141.46	93.35	149.03a	93.43	126.87a	92.96	132.49	95.64	2.944	.019	.01
Weeks	4.24	2.54	4.36	2.54	4.51a	2.49	3.98a	2.57	4.06	2.54	2.624	.033	.01
Grade	1.16	2.05	1.18	2.04	1.29a	2.13	0.87a	1.81	1.21	2.09	2.297	.057	.00

Results for the active weeks metric were also significant, $F(4,2054)=2.62$, $p=.033$, $\eta^2=.01$. Post-hoc comparisons using the Bonferroni correction indicated that the mean score for the Combined Mastery and Performance Goals profile ($M=4.51$, $SD=2.49$) was significantly different than for the Low Goals profile ($M=3.98$, $SD=2.57$). Profile differences in exam attendance were non-significant, $\chi^2(4)=6.75$, $p=.150$, C=.06.

Finally, achievement goal orientation profile did not significantly predict course grade, which consisted of programming points (50%) and exam grade (50%), $F(4,561)=1.50$, $p=.202$, $\eta^2=.01$.

5 DISCUSSION

5.1 Motivational Profiles

The objective of the present study was to identify the achievement goal orientation profiles present in a programming MOOC. Although there is already a large number of studies examining students' achievement goal orientation profiles and their associations with relevant academic outcomes, to our knowledge and based on recent literature review [24], there is no prior study using appearance and normative performance goals amongst mastery goals as the clustering variables.

We identified five distinct motivational profiles. The largest cluster, Approach-Oriented students, consisted of almost a third of the students. The profile is characterized by high mastery and normative performance goals, while appearance performance goals are low. Approach-Oriented students strive to master the content and perform well compared to other students. Mastery-Oriented students form the smallest cluster in the present sample (14%). While highly motivated by mastery, these students' scores in both performance orientations are the lowest of all profiles. Mastery-Oriented students strive to learn and master the course content but are not motivated by any normative comparisons. The remaining three clusters are students with Low Goals, students with Combined Mastery and Performance Goals and Performance-Oriented students. Performance-Oriented cluster can be characterized as seeking good performance and also appearing talented. They are separated from the Combined Mastery and Performance Goals group by a relatively weak interest to mastery. Finally, Low Goals group is characterized by relatively low scores on each of the orientations.

The number and nature of the identified profiles in the context of a programming MOOC were largely in line with prior studies conducted in different educational contexts; that is, we also found profiles characterized by predominantly mastery, predominantly performance, combined mastery and performance as well as low goals. In addition, applying the distinction into appearance and normative performance goals resulted in separating two groups of students equally striving for learning and outperforming others but differing in the goal for appearing competent; for students in the Approach-Oriented group, appearing competent was trivial, while for students in the Combined Mastery and Performance Goals group looking smart compared to peers was important. It is interesting that students in all groups scored rather high in mastery. The differentiation of appearance and normative performance goals seemed to yield meaningful motivational profiles, but further studies are still needed to establish their relevance.

Although Hakulinen and Auvinen have used a different achievement goal orientation framework, their study is closest match to us as they have applied person-oriented approach in a similar context [13]. Hakulinen and Auvinen identified four profiles: Success-Oriented (40%), Mastery-Oriented (28%), Indifferent (22%), and Avoidance-Oriented (10%). Their Success-Oriented and Mastery-Oriented profiles are similar to our Combined Mastery and Performance Goals and Mastery-Oriented profiles, correspondingly. The rest of the groups do not have clear counterparts. It's still interesting to note how the number of students with Combined Mastery and Performance Goals was clearly smaller in our case.

5.2 Performance and Goal Orientation

With regard to performance, students with Combined Mastery and Performance Goals stayed active on the course for longest and gained most programming assignment points, performing significantly better than students with Low Goals who dropped out earliest and gained less programming assignment points. Differences in performance between other profiles were non-significant.

When comparing the Combined Mastery and Performance Goals and Approach-Oriented profiles we noticed that while the mastery and normative goals go pretty much hand in hand, it is the appearance goal that distinguishes the profiles. As it turned out, Combined Mastery and Performance Goals profile, with its relatively high level of appearance goal, was the most advantageous profile in terms of academic achievement. Approach-Oriented profile, with a considerably lower level of appearance goal, did not differ from other profiles significantly.

It has been proposed that a combined mastery and performance goal profile, not a predominantly mastery-oriented profile, might serve as the most adaptive motivational pattern in terms of achievement outcomes for students in challenging and performance-focused educational contexts, such as higher education [24]. Regarding both Combined Mastery and Performance Goals and Mastery-Oriented profiles, our results seem consistent with previous studies conducted in such settings (e.g., [34, 35]). It is, however, important to note that, in the long run, striving for multiple goals (i.e., high performance goals alongside mastery) is linked not only with high achievement but also with vulnerability to emotional distress (e.g., stress, burnout [34]), which adds another viewpoint to the discussion on which orientation is good for what.

Another interesting perspective on our results is the effect of the appearance performance goal. Previous studies have shown appearance goals as negatively related or unrelated to educational outcomes [16], the latter also in CS context [41, 42]. Our findings, however, seem to not be in line with prior research, as our results show a significant positive – yet weak – correlation between the appearance goal and two performance metrics: programming assignment points and active weeks. Finally, the comparison of motivational profiles and performance is a timely topic as there is an increasing interest to use psychological measurements to predict and explain students performance also in computing education [15].

5.3 Contextual Factors

The context of the study is important to note as the goals of the students participating in a voluntary online course may differ from degree students. For example, Watted and Barak [39] observed that while degree students are oriented toward improving knowledge, non-affiliated students are interested about more specific career benefits. Despite differences in student populations, the same courses are still provided for both degree and MOOC students [21].

The findings of the present study contribute to the debate on which orientation is good for what and, more specifically, whether mastery or combined mastery and performance goals lead to better performance, in the context of a programming MOOC. In our analysis, mastery-oriented students did not stand out from the other groups. One potential explanation for this lies in the type and focus of the assignments of the course. The course uses a teaching approach that utilizes a large quantity of small assignments, which are well defined and automatically assessed. As mastery goals are often related to interest-based study strategy [30], which in turn is related to low performance in mostly closed-format exams, it is possible that another format of course assignments (e.g., small amount of large assignments) would be preferable to mastery-oriented students.

At the same time, there is evidence that smaller practice assignments support students learning the topic, and reduces the likelihood of postponing work [5]. This raises the question whether instructors taking a part of designing MOOCs should consider creating multiple versions of the course, where, on one hand, motivational profiles and, on the other hand, background and affiliation would be taken into account [17]. We argue that contextual factors might explain variation in the results related to the role of achievement goals in computing education [41], and that this should be addressed in future research.

In a broader sense, with the exception of a handful of studies (e.g., [1, 18, 40–42]), achievement goal orientations have been mostly studied outside of CS education research [24]. Acknowledging the challenges related to fitting existing frameworks and taxonomies into the CS education context [10, 20, 33], it is evident that there is a need to explore the fit of such theories to the CS education domain, in addition to the more prevalent topics (outlined e.g. in [22]).

5.4 Limitations of Work

Our study comes with a set of limitations, which we address next. First, we acknowledge sampling and selection bias due to the context of the study. The study has been conducted in a specific country and in a specific course, where students could choose whether they want to answer the questionnaire and whether they want to provide research consent. This limits the generalizability of our results, as demonstrated in the earlier work related to achievement goals in computing education [41]. Moreover, participation rate of the study was about 60%, and while we don't believe this has significant impact on the profiles per se, it is unclear how representative the proportional shares of the clusters really are.

Second, in the analysis of RQ2, we did not focus on previous programming experience due to space constraints. We acknowledge that previous programming experience often influences students' performance in introductory programming courses, and acknowledge that it is a confounding variable that influences the internal validity of our results. Third, as both the course assignments and the exam can be taken at a distance, it is possible that some students have received help as they work on the assignments while others may have not had access to such help. That is, students in the course may have had uneven access to help, which – even if their goal orientations are similar – may influence their success in the course.

6 CONCLUSIONS

In this work, we studied achievement goal orientations of over 2000 students participating in an introductory programming MOOC. While answering to our first research question, *What kinds of achievement goal orientation profiles can be identified among students participating in a programming MOOC*, we identified five distinct motivational profiles: Approach-Oriented who strive to master the topic and perform well, without a particular need to appear smart in front of others (31%), Performance-Oriented (i.e., seeking good performance and also appearing talented, 19%), Mastery-Oriented (i.e., interested in mastery, but not preoccupied with performance 14%), as well as students with Low Goals (i.e., having low scores in all of the measured motivational dimensions, 18%) and students with Combined Mastery and Performance Goals (18%). Profiles are somewhat similar to previous research, although the findings are unique as there are no prior studies using appearance and normative performance goals with mastery as the clustering variables.

Our answer to the research question 2, *Do students with different achievement goal orientation profiles differ with respect to their course performance*, indicates that although students with Combined Mastery and Performance Goals perform better than students with Low Goals, the differences are, all in all, small. In previous research, similar profiles characterized by striving for multiple goals have been related also to negative concomitants, such as stress and burnout. In our case, almost one fifth of the students were categorised as striving for multiple goals. This raises the questions of whether study material could be modified so that it would not guide towards potentially stressful study habits. Moreover, further research is needed to understand if motivational profiles between degree students and MOOC students differ also in online programming education, and whether this distinction could be used to adapt courses to different audiences.

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