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Self-initiated programming activity as a factor in developing students' skills in school education: Preliminary research findings

Submitted: 29.08.2023

Accepted: 01.04.2025

Published: 27.06.2025



Keywords:

self-activity,
programming activities,
programming,
education,
educational achievements

Abstract

Research objectives (aims) and problem(s): The study aims to examine the impact of secondary school students' programming activity on the development of specific skills in various areas of school education. It also seeks to identify factors that influence students' engagement in programming and the motivations behind their participation.

Research methods: The research was conducted in 2023 among 835 Polish students aged 15 to 19. A combination of quantitative methods was used, including frequency analysis with tabular summaries, measures of central tendency and dispersion, and statistical tests for group comparisons.

Process of argumentation: The study explores variations in students' programming engagement across different types of schools. It analyzes how participation in programming activities correlates with skill development and academic performance. Additionally, the research investigates factors that discourage students from programming and their specific areas of interest within the field.

Research findings and their impact on the development of educational sciences: The results show significant differences in students' engagement in programming activities. The primary motivations for participating in programming include skill development and academic success. The findings highlight the role of programming education in building digital competencies and confirm its relevance in contemporary education.

Conclusions and/or recommendations: The study underscores the importance of integrating programming into school curricula to support students' skill development. It also calls for further research on barriers to programming engagement and strategies to strengthen students' interest in this area.

Introduction

The life of a modern person – regardless of age – is closely tied to computer technologies, especially the products of programmers' work. Today, the majority of data processing relies on computers and specialized software tools. School education in programming offers a wide range of learning content, but to fully prepare students for the digital era, it is essential to introduce and develop computational thinking (Iskierka et al., 2015, p. 102). Programming has become a cornerstone of digital transformation, and it is impossible to imagine the modern world without digital systems. As dependence on technology continues to grow, programming has emerged as a key skill, with professionals in this field playing a vital role in the global economy (Konecki et al., 2023, p. 40).

In the context of contemporary education, it is crucial to define programming skills with precision. For the purposes of this study, programming skills are understood as a combination of three elements: proficiency in coding, problem-solving abilities (Kalelioğlu & Gülbahar, 2014, p. 47) and knowledge of specific programming languages. This definition is consistent with widely accepted views in the literature and ensures a clear and focused framework for the study's objectives.

A particularly important concept in this study is *computational thinking* (Zhou et al., 2022, p. 403), which encompasses a range of cognitive processes related to computer science, including problem-solving, system design, and understanding human behavior through computational principles (Xue & Zhun, 2020, p. 267). The essence of computational thinking lies in abstraction and automation (Barr & Stephenson, 2011, p. 51). In Wing's original formulation, computational thinking is described as a cognitive process that involves analyzing problems and developing solutions that can be executed efficiently by humans or computers (Wing,

2006, p. 33). This perspective underscores the importance of programming education beyond simply teaching coding to equipping students with transferable skills that are applicable across various disciplines (Labusch et al., 2019, p. 105).

Area, methodology and scope of research

Empirical research was conducted in February 2023 among secondary school students in the Lubelskie Voivodeship. In this study, *personal programming activity* was defined based on two criteria: (1) students' self-assessed frequency of programming engagement and (2) a binary classification distinguishing between those who engage in programming and those who do not. This dual approach allowed for an analysis of both the intensity and presence of programming activity among participants. A purposive sampling strategy was used to ensure diversity in school types, educational backgrounds, and levels of programming proficiency. The selection process was designed to minimize bias and provide comprehensive insights into students' programming engagement across different groups.

The demographic structure of the surveyed students is presented in the tables below.

This paper addresses the following research questions:

- What percentage of surveyed students engage in programming on their own?
- What are the goals and outcomes of students' self-directed programming activity?
- To what extent do students perceive programming skills as important and useful in the context of their school curriculum?

The distribution of respondents by gender is presented in Table 1 below.

Table 1. Demographic structure of the surveyed youth by gender

	Total	
	n	%
Gender		
Woman	366	43.83
Man	469	56.17
Age		
15–17	709	84.91
18–19	126	15.09
Place of residence		
Village	438	52.46
Small town	98	11.73
Large city	299	35.81
School type		
Comprehensive school	425	50.90
Technical school	410	49.10
Total	835	100

Source: Author's own research

Table 1 shows that the survey included 366 female students (43.83%) and 469 male students (56.17%). Among them, 709 participants (84.91%) were between the ages of 14 and 17, while 126 (15.09%) were between 18 and 19. Regarding place of residence, 438 respondents (52.46%) lived in rural areas, 98 (11.73%) in small towns, and 299 (35.81%) in large cities. In terms of school type, 425 respondents (50.90%) were attending general secondary schools, while 410 (49.1%) were enrolled in technical schools at the time of the survey.

Survey results are presented in tables summarizing response frequencies both overall and by subgroup. Frequency tables were used for nominal-scale data (Newcombe, 1998, p. 860), while ordinal data were described using the median for central tendency and the interquartile

range (IQR) for dispersion. Group comparisons were performed using the Wilcoxon-Mann-Whitney test for ranked data (Fay & Proschan, 2010, p. 10) and the Kruskal-Wallis test for variables with more than two categories (Douglas, 2017, p. 128). The equality of proportions test was used for analyzing nominal data (Newcombe, 1998, p. 858), while feature independence was assessed using Pearson's chi-square test (Agresti, 2006, p. 168). Student grades were compared using the Student's *t*-test.

For the purposes of this study, students' age, place of residence, and academic profile were categorized. Age groups were divided into 15–17 and 18–19 years, corresponding to when students typically take computer science courses in secondary school – differentiating those currently enrolled from those who had already completed the subject. Place of residence was grouped into small towns (cities with populations up to 5,000 and those with 5,000 to 10,000) and large cities (over 10,000 inhabitants). This classification was selected to simplify the analysis by grouping locations with comparable infrastructure and services. The population thresholds were defined according to the research context to capture urban diversity relevant to programming engagement and educational opportunities. Class profile categories were used to distinguish between science-focused and humanities-focused tracks. All statistical analyses were conducted using the R statistical software (2023).

The nature of the research and the main problem under investigation require the presentation of both dependent and independent variables, along with their respective indicators. Mieczysław Łobocki defines them as follows: "Dependent variable – the real or assumed effects observed in the examined studies of independent variables ... Independent variable – the factor that determines the nature of closer interactions in which the causes of specific changes in the process of upbringing, learning, or education are identified" (Łobocki, 2003, p. 142).

Accordingly, in the context of pedagogical sciences, the measurement used and the variables adopted in this study are not direct; that is, they cannot be observed outright. It is also important to emphasize that the operationalized indicators are reflected in the research tool that we developed.

Results of the author's empirical research

Table 2 presents the responses regarding students' self-initiated activity in programming.

Table 2. Declarations of self-initiated programming activity among the surveyed youth

Students' declarations of self-initiated activity in programming	Number of respondents	%
	No	572
68.5	Yes	263
31.5	Total	835

Source: Author's own study

The analysis of the results in Table 2 shows that fewer than one-third of respondents – 263 individuals, or 31.5% – reported engaging in their own programming activities. In contrast, more than two-thirds – 572 individuals, or 68.5% – stated that they do not participate in such activities. Table 3 presents the respondents' declarations regarding self-initiated programming activity, broken down by gender.

Table 3. Self-initiated programming activity among respondents – Comparison by gender

Students' declarations of self-initiated activity in programming	Gender				Total	
	Man		n		Total	Woman
	%	n	%	n	%	Yes
46	12.57	217	46.27	263	31.50	No
320	87.43	252	53.73	572	68.50	Total
366	100	469	100	835	100	Chi-square test
result: $p < .001$						

Source: Author's own study

The analysis of the results shows a significant difference between male and female respondents in their declarations of taking up programming activities. A substantially higher percentage of men (46.27%) reported engaging in programming on their own compared to women (12.57%). The numerical summary in the table reveals a statistically significant gender-based difference ($p < 0.001$) in self-initiated programming activities. Thus, it can be concluded that gender significantly influences students' engagement in programming.

Another important variable is the type of school, as it affects both the quality and focus of education. Table 4 presents data on students' declarations of participating in programming activities, broken down by school type.

Table 4. Self-initiated programming activity among respondents – summary by school type

Students' declarations of self-initiated activity in programming	School type				Total Comprehensive school	
	Technical school		n		%	Yes
	%	n	%	n		
71	16.71	192	46.83	263	31.50	No
354	83.29	218	53.17	572	68.50	Total
425	100	410	100	835	100	Chi-square test
result: $p < .001$ "						

Source: Author's own study

An analysis of the data in Table 4 reveals a significant difference between students attending comprehensive schools and those in technical schools. A greater percentage of technical school students (46.83%) report engaging in programming activities compared to students from comprehensive schools (16.71%). Statistical analysis ($p < 0.001$) confirms that the type of school significantly influences participation in programming.

The structure of school education is also shaped by the academic track. Table 5 presents data on students' declarations of self-initiated

programming activity, broken down by academic track among comprehensive school students.

Table 5. Self-initiated programming activity among surveyed comprehensive school students – summary by academic track

Students' declarations of self-initiated activity in programming	Academic track				Total Humanities	
	Science		n			
	%	n	%	n	%	Yes
12	8.28	59	21.07	71	16.71	No
133	91.72	221	78.93	354	83.29	Total
145	100	280	100	425	100	Chi-square test
result: p-value < 0.001						

Source: Author's own study

The data in Table 5 show that most students who engage in programming come from science-oriented classes (21.07%), while the majority of those who do not engage are from humanities classes (91.72%). Notably, a higher percentage of students from science classes (21.07%) reported pursuing programming activities compared to those from humanities classes (8.28%). The statistical analysis ($p < 0.001$) confirms that class profile significantly influences participation in programming activities.

Therefore, as follows from the above analyses of students' declarations, the variables of gender, type of school, and class profile significantly affect engagement in programming. However, the analysis shows no statistically significant influence from the variables of age and place of residence. Table 6 presents data on the specific areas in which the respondents engage in programming activities, broken down by gender.

**Table 6. Areas of self-initiated programming activity as reported
by students – by gender**

Self-initiatedprogramming activity area	Gender				Total	
	Woman		Man			
	n	%	n	%	n	%
Only during school lessons (various subjects)	13	28.26	24	11.06	37	14.07
Only outside of school	7	15.22	38	17.51	45	17.11
Both during and outside of school	26	56.52	155	71.43	181	68.82
Total	46	100	217	100	263	100
Chi-square test result: p = .009						

Source: Author's own study

Among female students engaged in programming, the majority reported participating in teaching, both inside (56.52%) and outside (28.26%) the classroom, while 15.22% reported involvement in extracurricular programming activities. In comparison, male students also prioritized learning (68.82%) inside and outside the classroom, with 17.11% participating in extracurricular programming and only 14.07% programming during school hours. A statistically significant gender difference ($p = 0.009$) was observed in the choice of programming activity areas.

Another research question concerns the characteristics of students' self-initiated programming activities, specifically their goals and outcomes. The starting point for the analysis was to identify the goals that motivate students to undertake programming independently. When completing the questionnaire, respondents were allowed to select more than one goal guiding their participation in programming. The goals listed in the table include acquiring programming skills, developing logical thinking, and nurturing a personal passion. Reported outcomes of such activities include achieving high grades, improving academic performance, and planning a future career as a programmer. In light of these findings, the study also examines the relationship between students' goals for programming and variables such as gender, age, place

of residence, type of school, and class profile. Table 7 presents data on students' declared goals for pursuing programming activities, categorized by place of residence.

Table 7. Declared goals for engaging in programming activities – by place of residence

Goals of self-initiated programming activity	Place of residence						Total	
	Village, N = 303		Small town, N = 93		Large city, N = 260			
	n	%	n	%	n	%	n	%
Achieving high grades	21	6.93	13	13.98	19	7.31	53	8.08
Improving school performance	34	11.22	6	6.45	18	6.92	58	8.84
Gaining programming skills	98	32.34	26	27.96	80	30.77	204	31.10
Developing logical thinking skills	53	17.49	13	13.98	64	24.62	130	19.82
Pursuing a personal interest	47	15.51	21	22.58	39	15.00	107	16.31
Planning a future career in programming	43	14.19	14	15.05	39	15.00	96	14.63
Other (please specify)	7	2.31	0	0.00	1	0.38	8	1.22
Total	303	100	93	100	260	100	656	100
Chi-square test result: $p = .032$								

Source: Author's own study

The analysis of the numerical summary presented in the table above shows a statistically significant relationship between place of residence ($p = 0.032$) and the goals and outcomes associated with programming activity. Therefore, it can be concluded that place of residence significantly influences the reasons for which students engage in programming. However, the analysis also reveals no statistically significant differences between gender ($p = 0.54$), age ($p = 0.2$), or class profile ($p = 0.4$) in relation to the goals and outcomes of programming activity.

Based on the above analysis of students' declared goals and outcomes related to their programming activity, it can be concluded that their

main motivations are skill acquisition. In terms of perceived outcomes, improving academic grades was partially confirmed. Most respondents cited acquiring programming and logical thinking skills as their main goals, while the most frequently mentioned long-term outcome was pursuing a career as a programmer.

The analysis in Table 7 shows that among students living in rural areas, the most commonly stated goal for engaging in programming activities is to acquire programming skills (32.34%). As for outcomes, the most frequently mentioned effect is the intention to pursue a career as a programmer in the future (14.19%). In small towns, the primary goal is also to acquire programming skills (27.96%), with the most frequently indicated outcome being a plan to become a programmer in the future (15.05%). Among students from large cities, the main goal is again to acquire programming skills (30.77%), while the most common intended outcome is a future career in programming (15.00%). The analysis reveals a statistically significant difference in programming-related goals and outcomes based on place of residence ($p = 0.032$). However, no significant differences were observed based on gender ($p = 0.54$), age ($p = 0.2$), or academic track ($p = 0.4$).

As a specific supplement to the main findings on students' programming-related goals, several respondents provided additional comments. Selected responses are presented below:

"I want to become a programmer in the future, so learning programming at home helps me gain more skills than what I get at school."

"I prefer learning programming at home because I can dedicate more time to it and even add a graphical interface to my programs."

"I want to learn programming, but in a different language. The one taught at school is outdated and of little use for the future."

"I'm just starting to learn programming. I'm not doing well at school, so I'm trying to catch up at home."

"I prefer learning from online tutorials on YouTube—there's more interesting and useful content there."

"I like programming. It's great to be able to create something useful."

“Programming is my passion and hobby. I hope to work in this field and earn a lot of money.”

“As soon as I get a programming job in Poland, I plan to move abroad to work in the profession.”

In the responses above, students indicate that school does not always meet their expectations regarding what they would like to learn in programming. They note that the curriculum often focuses on computer programs whose results are displayed via a console interface and lack a graphical interface. Another concern raised is that programming languages taught are outdated and rarely used in modern contexts. Respondents also pointed out that a key motivation for learning programming is the potential for high salaries and the opportunity to work in this profession abroad.

Based on the above analyses regarding the declared goals and outcomes of programming activities, the following conclusions can be drawn: in terms of goals, the surveyed group aims to acquire relevant competencies; in terms of outcomes, the goal of achieving higher grades is only partially confirmed. Most respondents expressed a desire to develop programming and logical thinking skills, while the most frequently indicated outcome was pursuing a career as a programmer.

Another specific area of investigation concerned the extent to which programming skills acquired in computer science classes are useful in other areas of schoolwork. To assess students' responses regarding the usefulness of programming skills in other school subjects, results were measured on an ordinal scale. The non-parametric Wilcoxon-Mann-Whitney test was applied. The grading scale used was as follows: 5 – very high, 4 – high, 3 – medium, 2 – low, 1 – not useful. Table 8 below presents the results of the Wilcoxon-Mann-Whitney test and the Kruskal-Wallis test regarding the perceived usefulness of programming skills in other school subjects, analyzed by gender.

**Table 8. Rank classification of the usefulness of programming skills
in other school subjects by gender**

Test result	Gender			p-value*
	Woman, N = 366	Man, N = 469		
Median (IQR)	2.00 (1.00; 5.00)		3.00 (1.00; 5.00)	< 0.001
Test result	Place of residence			p-value**
	Village, N = 438	Small town, N = 98	Large city, N = 299	
Median (IQR)	3.00 (1.00; 5.00)	3.00 (1.00; 5.00)	3.00 (1.00; 5.00)	0.001
Test result	School type			p-value*
	Comprehensive school, N = 425	Technical school, N = 410		
Median (IQR)	2.00 (1.00; 5.00)		3.00 (1.00; 5.00)	< 0.001
*Result of the Wilcoxon-Mann-Whitney rank test				
**Result of the Kruskal-Wallis test				

Source: Author's own study

The data in Table 8, with $p < 0.001$, indicates that programming skills have a statistically significant impact on other school activities when analyzed by gender. Similarly, in Table 8, with $p = 0.001$, programming skills also show a significant effect on the usefulness of other school activities based on the respondents' place of residence. This leads to the next research question: Do variables such as gender, place of residence, type of school, age, and class profile significantly differentiate respondents' assessments of the usefulness of programming skills in achieving school success – specifically in terms of knowledge, skills, attitudes, behaviors, and values?

Given that the responses related to the degree of usefulness of programming skills for school success were measured using an ordinal scale (ranks), the non-parametric Wilcoxon-Mann-Whitney test was applied. The data presented in Table 9 show the results of the Wilcoxon-Mann-Whitney test, assessing the declared degree of usefulness of programming skills for achieving school success, broken down by gender.

**Table 9. Rank classification of the usefulness of programming skills
for achieving school success – comparison by gender**

School achievement dimension	Gender		p-value*
	Woman, N = 366	Man, N = 469	
Knowledge	3.00(1.00;5.00)	3.00(1.00;5.00)	<0.001
Skills	3.00(1.00;5.00)	4.00(1.00;5.00)	<0.001
Attitudes	3.00(1.00;5.00)	3.00(1.00;5.00)	<0.001
Behaviors	2.00(1.00;5.00)	3.00(1.00;5.00)	<0.001
Values	2.50(1.00;5.00)	3.00(1.00;5.00)	<0.001
*Result of the Wilcoxon-Mann-Whitney rank test			

Source: Author's own study

Gender significantly influences how respondents assess the usefulness of programming skills for academic achievement, with notable differences observed in the areas of knowledge ($p < 0.001$), skills ($p < 0.001$), attitudes ($p < 0.001$), behavior ($p < 0.001$), and values ($p < 0.001$). However, respondents' age does not significantly impact their assessment of the usefulness of programming skills for school achievement, as indicated by the following p -values: knowledge ($p = 0.2$), skills ($p = 0.3$), attitudes ($p = 0.7$), behavior ($p = 0.7$), and values ($p = 0.13$). The data presented in Table 10 show the results of the Wilcoxon-Mann-Whitney non-parametric test assessing the declared usefulness of programming skills in achieving academic success, taking into account the type of school.

**Table 10. Rank classification of the usefulness of programming skills
for academic achievement – comparison by type of school**

School achievement dimension	School type		p-value*
	Comprehensive school, N = 425	Technical school, N = 410	
Knowledge	3.00 (1.00; 5.00)	3.00 (1.00; 5.00)	< 0.001
Skills	3.00 (1.00; 5.00)	4.00 (1.00; 5.00)	< 0.001
Attitudes	2.00 (1.00; 5.00)	3.00 (1.00; 5.00)	< 0.001
Behaviors	2.00 (1.00; 5.00)	3.00 (1.00; 5.00)	< 0.001
Values	2.00 (1.00; 5.00)	3.00 (1.00; 5.00)	< 0.001
*Result of the Wilcoxon-Mann-Whitney rank test			

Source: Author's own study

The analysis of the data in Table 10 indicates that the type of school attended by the respondents significantly influences their assessment of the usefulness of programming skills for academic achievement. This effect is observed across all evaluated domains – knowledge, skills, attitudes, behavior, and values – with all p-values less than 0.001. Additionally, place of residence significantly differentiates respondents' views on the usefulness of programming skills in terms of knowledge ($p = 0.014$) and skills ($p = 0.010$). However, when it comes to attitudes ($p = 0.9$), behaviors ($p = 0.5$), and values ($p > 0.9$), respondents from different locations tend to assess the usefulness of programming skills similarly.

Regarding academic track, it significantly affects respondents' assessments of the usefulness of programming skills in acquiring knowledge ($p = 0.011$). However, for skills ($p = 0.095$), and for attitudes, behaviors, and values (all $p > 0.9$), respondents from different class profiles reported similar evaluations. To summarize the findings on how programming skills contribute to students' academic success: in terms of knowledge, respondents rated the usefulness of programming skills at a moderate level; in terms of skills, at a low level; and in terms of attitudes, behaviors, and values, at a high level.

It is essential to organize classes that help students understand the benefits and advantages of learning programming – especially how programming skills can be applied in various academic contexts. Raising awareness about the wide applicability of programming in daily life, as well as its potential use in other school subjects, may positively influence students' academic performance. Since the desire to acquire programming skills is a key factor motivating students to engage in programming, it is important to foster the development of young people's values and norms in this area.

Conclusions

The research results presented here show that nearly one-third of the surveyed students engage in their own programming activities. This can be considered at least a satisfactory outcome, particularly since the study group was not limited to students from computer science-focused classes. This suggests a diverse interest in programming, influenced by both class and school type. Students from technical secondary schools and science-track classes were much more likely to report engaging in their own programming activities than those from general education schools and humanities-track classes.

In terms of goals, students' self-directed programming activities were mainly driven by a desire to build competencies, while the effect of achieving higher grades was only partially confirmed. The results of the Wilcoxon-Mann-Whitney non-parametric test for rank classification show that the surveyed students perceive programming skills as having a medium to high level of usefulness in other school subjects.

Programming education plays a vital role in the advancement of modern information technology and in shaping various aspects of human life. It not only addresses current demands, but also constitutes a key driver for development across all areas of human activity. As such, education in this field is essential. Recognizing these needs allows government institutions to exercise statutory oversight of programming education for children and school-age youth.

The findings presented in this study suggest the need for further, more in-depth research to better understand the disparities observed between schools and the factors influencing students' engagement in programming. The next phase of this research will involve examining not only the reasons behind students' decisions not to engage in programming activities, but also the potential structural or environmental barriers contributing to these choices. Additionally, the study will examine the nature of students' self-directed programming activities, the types of programming tasks that they undertake both in and outside of school, and the relationship between educational settings and individual interests in programming. These efforts will allow for a more nuanced interpretation of the results and a deeper exploration of the underlying mechanisms.

Funding: This research received no external funding.

Conflicts of Interest: The author declares no conflict of interest.

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