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Students' Perceptions of Distance Learning During COVID-19—Investigating Predictors Among Learning Behavior, Family Background and Demographic Characteristics

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Abstract

COVID-19-related school closures substantially disrupted students' daily lives. While prior research has predominantly relied on externally assessed achievement data and proxy indicators of well-being, less is known about students' own perceptions of their experiences during distance learning. This study addresses this gap, using a qualitatively informed quantitative analysis. First, open-ended responses from $N = 698$ students from German and Swiss schools were analyzed to identify perceived positive and negative aspects of distance learning, thereby providing experience-based indicators of how the pandemic affected students' well-being. Quantitative content analysis revealed that students most frequently mentioned advantages such as being at home and experiencing greater independence, while common disadvantages included a lack of social contact and insufficient learning support. Second, random forest models were applied to identify individual, contextual, and background-related predictors of these perceptions. Students with stronger self-regulation skills, lower levels of procrastination, and better-equipped home learning environments were more likely to emphasize positive experiences. Conversely, younger students and those with weaker self-regulation and fewer home learning resources more frequently reported negative experiences. The findings reveal substantial variability in students' perceptions of distance learning, shaped by learner-related, contextual, and broader background factors. They underscore the importance of fostering self-regulation and ensuring equitable access to learning resources to better prepare schools for future crises.

Keywords: distance learning; COVID-19; students' well-being; teaching under crisis conditions; individual learning prerequisites

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1. Introduction

School closures during the COVID-19 pandemic posed major challenges for all stakeholders in the school system. Students and teachers had to adapt rapidly to unfamiliar forms of teaching and learning. Previous research has documented declines in learning outcomes [1,2], reduced well-being [3,4], and lower life satisfaction [5] among students. As this evidence is based primarily on externally assessed performance data and proxy indicators of well-being, less attention has been paid to students' own perceptions of their experiences during distance learning [6].

However, students' perspectives are crucial, given that well-being is a highly subjective, multi-dimensional phenomenon [7,8]. According to Diener's definition [9] and the

related bottom-up-theory [10], well-being is shaped by the accumulation of positively and negatively perceived experiences and emotions. Consequently, well-being is reflected not only in global judgments, but also in how individuals appraise concrete experiences in everyday life. By examining both positively and negatively perceived aspects of distance learning, students' subjective evaluations may provide an experience-based perspective on the mechanisms through which school closures affected their well-being [11].

At the same time, students' subjective evaluations of distance learning were unlikely to be homogeneous, as they differed considerably in how they coped with and adapted to pandemic-related restrictions depending on individual and contextual conditions [12]. Although recent studies indicate that students from families with lower socioeconomic status (SES) and those with weaker independent learning habits experienced greater difficulties in terms of learning and well-being [1,12–14], findings on which students adapted most effectively and which were particularly vulnerable remain incomplete and partly contradictory [15–17]. To investigate these differences more systematically, the present study draws on integrative models of student well-being, which conceptualize well-being as a multidimensional construct shaped by individual characteristics, contextual conditions, and broader background variables [18–20]. Across these frameworks, student well-being is understood as emerging from the interplay of intrapersonal dispositions, engagement-related processes, and environmental factors.

Against this theoretical background, the present study does not assess well-being directly but focuses on the positive and negative aspects of distance learning identified by students themselves, conceptualizing these subjective evaluations as experience-based indicators of their well-being during school closures [8,21–23]. At the same time, drawing on multidimensional models of student well-being, these perceptions are understood as shaped by the interaction of learner-related, contextual, and broader background factors. In line with the theoretical considerations outlined above, three groups of factors are considered as potential predictors of these perceptions: first, individual learning behavior—including self-regulation, procrastination, and perceived learning success—as indicators of intrapersonal and engagement-related processes; second, contextual conditions of the home learning environment—such as available resources and indicators of socioeconomic and cultural capital—as external and structural influences; and third, demographic and schooling-related characteristics—including age, gender, migration-related background, and country of schooling—as more distal factors. Together, these factors capture multiple, interrelated levels of influence that may shape how students experienced and evaluated distance learning.

To capture students' subjective perspectives as experience-based indicators of their well-being, while also examining how these perspectives were shaped by individual, contextual, and background factors, the present study applies a *qualitatively informed quantitative analysis* [24,25] to examine students' perceptions of distance learning during COVID-19-related school closures. In a first step, quantitative content analysis [26] was used to code open-ended responses from $N = 698$ students from Germany and Switzerland regarding positively and negatively perceived aspects of distance learning. In a second step, based on the resulting coded data, random forest models [27] were used to analyze the predictive role of learning behavior, the home learning environment, and sociodemographic characteristics on the likelihood of mentioning specific positive or negative aspects.

The results provide a more differentiated understanding of how the pandemic affected students and offer insights into how future distance learning situations can be designed in ways that better address students' needs. Although the COVID-19 pandemic has largely subsided, future disruptions caused by disease outbreaks [28] or extreme weather

events [29] remain likely. To avoid negative outcomes in such cases, lessons from the COVID-19 pandemic should inform future preparedness.

2. Empirical and Theoretical Background

2.1. Teaching During the COVID-19 Pandemic

At the onset of the COVID-19 pandemic, schools were abruptly required to shift instruction from classrooms to students' homes through digital media—often without prior preparation or experience. This rapid transition in many cases resulted in a form of teaching characterized by a high degree of independent student work and limited direct communication between teachers and learners, although direct interaction has been found to be a key component of effective distance learning [30]. For students, these changes substantially altered everyday learning experiences [31] and likely shaped how distance learning was perceived and evaluated. Globally, numerous studies documented stagnation or declines in student learning outcomes during this period [1,2]. Instruction relied heavily on digital tools [31,32]; however, many teachers assessed their digital competence as insufficient [33].

From the perspective of scaffolding theory, the reduction in direct communication between teachers and students limited opportunities for cognitively demanding intermental and social learning processes—such as modeling, guided practice, and interactive feedback—thereby shifting the learning emphasis toward intramental activities like summarizing and repetition [34]. The reliance on self-directed learning posed particular challenges for students with lower self-regulatory skills, contributing to reduced learning success [14]. In addition, daily learning time decreased considerably [31,35], and many students reported a lack of teacher feedback, making it difficult to assess their own progress [36].

Empirical findings indicate that the effects of distance learning were not evenly distributed across student groups. Regarding gender, some studies report that female students experienced greater learning losses [37–39], whereas others found no significant gender differences [40,41]. Under regular circumstances, female students tend to display higher academic self-concept and learning motivation [42,43], while male students often report greater self-efficacy when engaging with digital technologies [44].

Age-related findings are more inconsistent. Some studies suggest that older students benefited from more advanced self-regulation skills [45,46], whereas others indicate that they faced greater difficulties due to more complex curricula and increased examination pressure [47,48]. Furthermore, students with a migrant background often encountered greater learning difficulties, which may be attributed to language barriers, unfamiliarity with the school system, or limited academic support at home [1,49].

Socioeconomic characteristics also played a substantial role. Students from socioeconomically disadvantaged families frequently lacked quiet workspaces or appropriate digital equipment, hindering their participation in online learning [36,50]. Conversely, parents with higher educational levels were generally better able to support their children's learning, fostering more positive outcomes [51,52]. Cross-country comparisons further reveal that learning losses correlated with the duration of school closures, with wealthier nations—where closures tended to be shorter—reporting fewer learning losses [53,54]. Taken together, these findings suggest that students' experiences of distance learning were shaped by multiple levels of influence, including instructional and home-learning conditions, individual learning-related characteristics, and broader demographic background factors.

As indicated above, students' individual perceptions of distance learning have received only limited attention. The few previous studies that examined students' perceptions

typically relied on small, targeted samples and often focused on university students rather than school students.

Some of these studies concluded that, from students' perspective, understanding instructional content emerged as a major challenge. Approximately 40% of students in a Swiss survey reported difficulties comprehending learning materials provided during distance learning [55]. This lack of understanding was closely linked to emotional strain: in a German study, around one-third of students expressed concern about their academic progress and qualification attainment [56].

Many students also cited limited opportunities to ask questions and insufficient clarity in instructional delivery [57], which contributed to feelings of detachment from schoolwork. Excessive workload, combined with the need for self-regulated learning, was frequently reported as overwhelming. Moreover, social isolation was a pervasive issue, as the absence of peer interaction diminished motivation and well-being [57,58]. Students also criticized the lack of practical or hands-on learning, particularly in subjects that depend on experiential activities [58]. Technical and infrastructural challenges—such as unstable internet connections—further disrupted the learning process [59]. Overall, many students perceived a mismatch between instructional demands and their capacity for autonomous learning [60].

Despite these difficulties, students also identified several positive aspects of distance learning. Many appreciated the flexibility in managing their time and the opportunity to learn at their own pace [58,60,61]. Additional benefits included longer sleep times and the elimination of commuting [31,57].

Structurally, students reported improved access to and organization of teaching materials [57,60]. The digital availability of content facilitated independent review and planning, while the use of digital learning tools—such as educational apps, quizzes, and structured online lectures—was positively evaluated for enhancing engagement and comprehension [59]. Other advantages included fewer distractions, greater access to parental support, and increased autonomy in organizing one's learning process [57]. For some students, these features contributed to a learning environment perceived as more efficient and manageable.

2.2. Student Well-Being During the COVID-19 Pandemic

As outlined above, student well-being during the pandemic can be understood as a multidimensional construct reflected not only in global judgments, but also in students' appraisals of concrete everyday experiences (cf. Section 1). Against this background, the restrictions associated with the pandemic significantly affected multiple domains of students' well-being [4]. Increased stress and decreased life satisfaction were widely reported [5], alongside heightened peer-related problems, hyperactivity, and confrontational behavior [62], as well as increased levels of anxiety and depression [63]. School closures removed both students' structured learning environment and an important space for peer interaction that cannot be replaced within the family environment [64]. The loss of these elements negatively affected students' well-being [65,66]. Social interaction is known to function as a protective factor against mental illness [67,68] and contributes to fulfilling the basic need for relatedness, which in turn influences learning motivation [69]. Poor learning outcomes and difficulties with self-regulation may undermine students' sense of competence and autonomy, thereby further reducing well-being [14,69].

The loss of daily structure also contributed to reduced student well-being [70,71]. Managing everyday demands required strong self-regulatory skills. According to the eudaimonic perspective on well-being, difficulties in this domain may impair individuals' sense of personal growth [72]. Furthermore, problems in structuring the day can lead to procrastination. Although procrastination may temporarily protect self-esteem [73], it is

associated with long-term negative outcomes such as reduced sense of meaning [74], lower self-esteem, and diminished self-control [75]. Procrastination is also correlated with anxiety, depression, and reduced positive affect [14,76].

The suspension of extracurricular activities further weakened students' physical and psychological resilience [4,77]. In addition, many students perceived the monotony of home-based learning and limited availability of recreational activities as burdensome [78].

Regarding demographic differences in well-being, female students reported higher levels of stress and anxiety than male students [13,64]. A study of German students found that the proportion of female students with depressive symptoms increased from 13% before the pandemic to 35% in spring 2020 at the onset of the pandemic, while the proportion among male students increased from 7% to 15% during the same period [64].

Findings regarding age differences are mixed. Some studies suggest that younger students suffered more due to difficulties maintaining peer contact [79,80]. Other studies argue that older students were at greater risk of loneliness due to disrupted social transitions [81] and therefore experienced stronger negative effects of the restrictions [13].

Students with a migration background also reported lower levels of well-being [82], which may partly be explained by a higher prevalence of perceived loneliness [83]. SES likewise affected students' wellbeing: Students from wealthier families reported higher levels of well-being, supported by better learning conditions and fewer financial concerns within the family [84–86]. Cross-country comparisons further indicate that students in countries with shorter school closures and less restrictive containment measures, such as Switzerland [87,88], reported higher levels of well-being than students in countries where restrictions were stricter, such as Germany [13,89].

Taken together, these findings can be linked to the integrative models of student well-being (cf. Section 1), suggesting that students' well-being during the pandemic was shaped by the interplay between individual learning behavior, contextual conditions of the home learning environment, and demographic background characteristics. This framework provides the basis for examining students' perceptions of distance learning as experience-based indicators of their well-being during school closures.

3. Research Questions

Given the limited research on students' individual perceptions of distance learning during the COVID-19 pandemic, the present study first conducted a qualitative investigation to identify aspects of distance learning that students perceived as positive or negative. In line with the bottom-up theory of well-being [10], this approach captures experience-based indicators of students' well-being through their subjective appraisals of concrete learning experiences rather than through global judgments. By examining open-ended responses to both positively and negatively perceived aspects of distance learning, the study enables an exploratory analysis of students' subjective perspectives in which themes can emerge inductively rather than being constrained by predefined response categories. In this way, the study offers an experience-based perspective on how school closures may have been reflected in students' appraisals of their learning experiences, thereby providing experience-based indicators of how the pandemic may have affected their well-being [8,21–23].

For this, the following research question (RQ) was explored:

- RQ1: Which aspects of distance learning during the COVID-19 pandemic were perceived positively or negatively by students?

Building on the aspects of distance learning identified in the first step, the second step examined whether students' subjective perceptions differed across theoretically relevant student characteristics. For this purpose, the qualitative categories derived from the open-

ended responses were used as the basis for a *qualitatively informed quantitative analysis* [24,25]. In line with the integrative model of student well-being outlined above, learning behavior, family background, and demographic characteristics were considered as predictor domains representing intrapersonal and engagement-related processes, contextual conditions of the home learning environment, and broader background variables. This step therefore extended the exploratory identification of positively and negatively perceived aspects by investigating whether the likelihood of mentioning these aspects differed across these predictor domains.

The following RQs were addressed for this:

- RQ2: To what extent do aspects of learning behavior, family background, and demographic characteristics predict the likelihood that students mention specific positively perceived aspects of distance learning?
- RQ3: To what extent do aspects of learning behavior, family background, and demographic characteristics predict the likelihood that students mention specific negatively perceived aspects of distance learning?

4. Methodological Approach

To address the research questions, a secondary analysis was conducted using data from the student questionnaire *My Corona Diary*. The questionnaire was administered online via SoSciSurvey [90] in German. The survey link was distributed to students in Germany, Austria, and Switzerland through mailing lists, the mailing list of a commercial platform, as well as professional and personal networks. Teachers and students affiliated with these networks were additionally invited to forward the link within their own networks. Data collection occurred between 5 April 2022 and 22 July 2022. Due to limited personal contact with Austrian schools and administrators, only three students from Austria completed the questionnaire. As a result, the analyses were confined to students from Germany and Switzerland.

4.1. Sample

This study analyzed data from $N = 698$ students from various grade levels and school types in Germany and Switzerland, aged between 6 and 24 years ($M = 15.95$, $SD = 2.19$). This total sample refers to all students who responded to at least one of the two open-ended questions: $n = 635$ students responded to the question "What did you like about distance learning? What do you think could stay the same?", and $n = 637$ students responded to the question "What did you not like about distance learning?". The wide age range reflects the exploratory aim of the study to capture diverse student experiences across educational stages. However, this heterogeneity must be taken into account when interpreting the findings, as developmental differences may influence both learning behavior and perceptions of distance learning. The composition of the sample is presented in Table 1. The inclusion of students from Germany and Switzerland is informative, as both countries have comparable school systems, including a federal organization, similar durations of compulsory education, and a multi-track secondary structure. Both countries are also classified as high-income. Nevertheless, during the COVID-19 pandemic, containment measures in Switzerland were less restrictive, and school closures were shorter than in Germany [87,88]. Considering other influencing factors, these conditions may help to contextualize differences in students' perceptions against the background of differing containment strategies between the two countries.

Table 1. Sample composition.

Variable	Germany		Switzerland		Total	
	n	%	*n*	%	*n*	%
Gender [a]						
Female	403	70.8	71	55.0	474	67.9
Male	166	29.2	58	45.0	224	32.1
First language						
German	427	75.0	101	78.3	528	75.6
Other language than German	142	25.0	28	21.7	170	24.4
Level of schooling						
Primary school [b]	7	1.2	2	1.6	9	1.3
Lower secondary school	314	55.2	124	96.1	438	62.7
Upper secondary school	248	43.6	3	2.3	251	36.0
Total	569	81.5	129	18.5	698	100

[a] Students also had the opportunity to rate their gender as non-binary. None of the examined students rated their gender as non-binary. [b] It should be noted that primary school in Switzerland lasts until the 6th grade, whereas in most federal states in Germany it only lasts until the 4th grade.

4.2. Survey Instrument

To address RQ1, responses to the two open-ended questions "*What did you like about distance learning? What do you think could stay the same?*" and "*What did you not like about distance learning?*" were analyzed using an inductive coding approach for open-ended responses (cf. Section 4.3). The use of open-ended questions enabled an exploratory analysis of students' subjective perspectives, allowing themes to emerge inductively rather than being constrained by predefined response categories. Consequently, well-being was not assessed through direct measurement; instead, students' subjective perceptions of distance learning were used as experience-based indicators of well-being [8], in line with Diener's bottom-up theory [10], which conceptualizes well-being as arising from individuals' evaluations of specific life domains (cf. Section 1). The coding of these responses served to derive an empirically grounded category system of positive and negative aspects of distance learning, which then informed the subsequent quantitative analyses.

To address RQ2 and RQ3, additional scales and items were analyzed:

Learning behavior was assessed using three variables: self-assessed *self-regulation*, self-assessed *learning success*, and tendency of *procrastination*.

- Students' self-assessed *self-regulation* was measured on a 4-point scale (1 = *not at all*, 4 = *exactly*) using 9 items (e.g., "*I set learning goals for myself*"), based on Zimmerman (2006) and adapted by Toering et al. (2012) [91,92]. Toering et al. (2012) provided evidence of content and construct validity as well as satisfactory test-retest reliability and internal consistency ($\alpha = 0.827$) [91].
- Students' self-assessed *learning success* was assessed with a focus on mathematics using the question "*How do you assess your learning progress in math in distance learning compared to face-to-face teaching?*". Responses were given on a 5-point scale (1 = *not good at all*, 5 = *very good*).

Mathematics was chosen because it is a core academic subject and a central domain of school learning. In educational research, mathematics achievement is frequently used as an indicator of academic development, as it is closely linked to general academic success, cognitive abilities, and later educational outcomes [93,94]. Thus, mathematics provides a suitable and widely accepted proxy for broader learning processes [95]. In addition, mathematics learning is strongly cumulative, so disruptions in instruction may become particularly visible in this subject. This makes mathematics a useful domain for assessing

students' perceived learning progress during distance learning. At the same time, it should be noted that this measure captures students' perceived learning success in a specific subject rather than their overall learning experience.

- Students' tendency of *procrastination* was measured using 8 items (e.g., "*Please estimate how often you distract yourself from working*") on a 5-point scale (1 = *never*, 5 = *always/regularly*). The items were taken from the German version of the *APSI-d* scale [96]. Patzelt and Opitz (2005) reported evidence of convergent and divergent validity as well as criterion validity for the original scale and high internal consistency ($\alpha = 0.890$) [96].

The operationalization of learning behavior is grounded in self-regulated learning theory, which conceptualizes learning behavior as a multidimensional construct encompassing cognitive, metacognitive, motivational, and volitional components [97]. In line with self-regulated learning theory, the three variables represent complementary aspects of learning behavior. Self-regulation captures strategic and motivational control, procrastination reflects deficits in volitional regulation, and self-assessed learning success represents learners' evaluative and efficacy-related reflections on their outcomes.

Students' home learning environment was assessed using the following three indicators:

- Students' *workplace equipment* was measured using six dichotomous items assessing the availability of resources at the home workplace (e.g., a quiet room, a computer). Responses were coded as *available* (0) or *not available* (1).
- Students' *household equipment* was measured using seven items assessing the number of selected household assets (e.g., cars, computers). Response categories ranged from "*none*" (1) to "*three or more*" (4).
- The *number of books* in students' households was measured using the single item "*How many books do you have at home?*" answered on a seven-point scale from 1 = "*none or very few (0–10)*" to 7 = "*enough to fill several shelves in a room (more than 301)*".

The frequency variables *household equipment* and *number of books* were treated as continuous variables, as recommended by Robitzsch (2020) [98] and were included in the analyses as continuous predictors. The examined variables represent widely used proxy measures of students' socioeconomic background. As SES is a latent construct that cannot be directly observed [99], it is commonly approximated in large-scale assessments through indicators of material and educational resources available in the home environment.

In this context, household equipment captures aspects of material resources, whereas the number of books is typically interpreted as an indicator of cultural capital [100,101]. Both measures were drawn from the Home Educational Resources Scale and the Cultural Possessions Scale used in the PISA 2018 student questionnaire [102] and were selected based on their discriminatory power and relevance to learning during the pandemic. Although these indicators provide only an approximation of SES, their use follows established practice in educational research and allows for a parsimonious and internationally comparable assessment of students' socioeconomic and cultural background.

Additionally, the following demographic factors were assessed:

- *Gender* (0 = *female*, 1 = *male*)
- Students' *age* (in years)
- *Country of schooling* (0 = *Germany*, 1 = *Switzerland*),
- Students' *first language* (0 = *other language than German*, 1 = *German*).

4.3. Analyses

To address RQ1, students' responses to the two open-ended questions were analyzed in MAXQDA (version 24.7.0) [103] using *quantitative content analysis* [26], an approach

well suited for the systematic examination of large numbers of short written survey responses [104]. This method enabled the identification and quantification of recurring themes in the textual material while remaining closely grounded in students' own wording and perspectives.

An inductive code tree was developed based on a random 30% subsample of the responses. First, the subsample was reviewed repeatedly to identify recurring aspects in students' statements. On this basis, an initial hierarchical coding scheme was developed by first generating main categories and subsequently refining them through the creation of corresponding subcategories. The preliminary code tree was discussed and reviewed within the research team [105] and slightly refined during the subsequent coding process to clarify category boundaries and resolve overlaps. This inductive procedure ensured that the coding framework remained closely grounded in students' own expressions and perspectives rather than being shaped by predefined theoretical categories [106]. For each open-ended question, six main categories with up to eight subcategories were identified. The full coding tree is presented in Appendix A (Table A1).

Coding was initially conducted independently by two raters and subsequently discussed using a *consensus coding procedure* [107]. Discrepancies were resolved through discussion until agreement was reached, with the aim of clarifying ambiguous responses, sharpening category definitions, and establishing a shared understanding of code application. This procedure was considered appropriate because the coding tree was developed inductively and refined iteratively throughout the analytic process [108]. Accordingly, consensus discussions supported both the consistent use and the ongoing refinement of the coding scheme while remaining aligned with the exploratory nature of the analysis. Rather than prioritizing a formal coefficient of intercoder agreement, the approach emphasized the iterative refinement and transparency of coding decisions, which was considered more appropriate for an inductively developed and iteratively refined coding framework [109].

As prior research on surveying adolescents indicates that developmental differences in communication, reading skills, and response behavior often result in very short open-ended responses among younger respondents [110], each meaningful statement—including individual keywords—was treated as a coding unit. Multiple coding of individual statements was permitted. After coding, category frequencies were calculated to identify which positive and negative aspects of distance learning were mentioned most frequently by students. This approach enabled an exploratory analysis of students' subjective perspectives by allowing themes to emerge inductively rather than being constrained by predefined response categories. Given the large number of short written statements, this procedure allowed us to capture whether specific aspects were present in students' responses, while acknowledging that the brevity of many responses limited the extent to which broader narrative context or intensity could be reconstructed. For the same reason, the data were less suited to an in-depth qualitative reconstruction of individual meaning-making, which typically requires more extensive and context-rich accounts. Thus, the first analytic step provided an empirically grounded and systematically describable category structure that remained close to students' own wording and could be used as the basis for the subsequent quantitative analyses.

To answer RQ2 and RQ3, a *qualitatively informed quantitative analysis* was conducted, in which the coded open-ended responses were transformed into analyzable variables for subsequent statistical modeling [24,25]. This transformation of coded qualitative material into numerical indicators can be described as 'quantitizing' [25]. For this purpose, the five most frequently mentioned positive and negative aspects were coded as "1" (mentioned by the student) and "0" (not mentioned). These binary indicators captured whether a given theme was present in a student's response, thereby enabling systematic comparisons across

individuals. At the same time, this operationalization was not intended to preserve the full interpretive richness of the open-ended responses, as it does not capture the intensity, contextual meaning, or co-occurrence of themes. We focused on the five most frequently mentioned positive and negative aspects because these categories represented the most robust recurring themes in the dataset, showed sufficient prevalence for stable quantitative modeling, and enabled a parsimonious comparison across individuals.

Random forest models [27] were used to assess the predictive value of learning behavior, equipment of the home environment, and demographic characteristics in predicting whether students mentioned a specific coded aspect in their open-ended responses. Random forest models for classification train ensembles of decision trees on bootstrapped data samples, using a random subset of features at each split. The final predicted class is determined by aggregating individual tree predictions via majority voting. Variable importance is quantified based on each predictor's contribution to overall predictive accuracy or node purity [111,112]. The models were estimated in R (version 4.5.3) [113] using the R-package *H2O* [114].

To address the strong imbalance in the dependent variables (with value 0 occurring much more often than 1), random oversampling (ROS) was applied [115] using the R-package *ROSE* [116]. Model hyperparameters were tuned to improve prediction accuracy [117] using the R-package *caret* [118]. The performance of the random forest models was evaluated based on mean squared error (*MSE*), area under the receiver operating characteristic curve (*AUC*), and the *Gini coefficient*. *MSE* indicates the average squared difference between predicted and actual values and was used to assess the predictive accuracy of the models [119]. It can take values from 0 to 1, with values closer to 0 indicating better predictive performance [120]. In classification settings, *MSE* values between 0.15 and 0.35 are considered realistic and good [121]. *AUC* evaluates the ability of a random forest classifier to distinguish between classes by measuring the area under the receiver operating characteristic (ROC) curve [122]. It ranges from 0 to 1, with values between 0.8 and 0.9 considered good and values above 0.9 considered very good [122]. The *Gini coefficient* reflects the purity of the nodes in the random forest and indicates the probability of a particular variable being misclassified when selected at random [119,123]. It can be derived directly from the *AUC* using the formula $Gini = 2 \times AUC - 1$ [124]. Accordingly, the threshold values for the *Gini coefficient* are based on those of the *AUC*, with values above 0.6 interpreted as good and values above 0.8 as very good [122].

The importance of the examined variables was assessed using *absolute variable importance* (*VI*) and *percentage contribution to total variable importance* (*%VI*). *VI* provides absolute values within a given model, indicating the relative predictive contribution of a particular predictor compared with the other predictors in the same model [125]. *%VI* indicates the percentage share of the total variable importance accounted for by each predictor [123]. It can therefore be used to compare the importance of predictors across different models. As there is a lack of empirically established thresholds for interpreting variable importance values [126,127], their evaluation necessarily relies on heuristic criteria [128]. This is particularly the case for *%VI*, which is a relative importance measure that ranks predictors according to their proportional contribution to overall model performance [123,129]. Because such measures are normalized and interpreted comparatively rather than absolutely, their evaluation does not follow theoretically defined cutoffs but instead requires pragmatic decisions about what constitutes a non-negligible contribution [123,129].

In prior research, heuristic thresholds for normalized importance measures have often been set in the range of 0.05 to 0.10 to distinguish predictors of substantive relevance [130–132]. Following this practice and given the exploratory pattern-detection aim of the present study, we adopted the more conservative upper bound of this range ($\%VI > 0.10$). This stricter criterion was chosen to enhance the clarity and parsimony of the

analyses and to reduce the risk of overstating predictors that showed only minor relative contributions within the random forest models. Accordingly, the threshold is not understood as a formally established cutoff, but rather as a pragmatic and heuristic decision rule that helps identify variables with comparatively meaningful relative importance while avoiding an overly inclusive selection.

Random forests were chosen to assess the research question because they are more robust to outliers and multicollinearity and tend to perform well in exploratory settings relative to traditional regression approaches [111]. In addition, they allow the modeling of complex, non-linear relationships between multiple predictors and students' perceptions [133]. Consequently, in exploratory contexts, machine learning approaches such as random forests can offer advantages over conventional regression models [133].

However, variable importance measures derived from random forests do not provide information about the direction or functional form of predictor effects. To address this limitation, we complemented the analysis of the predictors with a $\%VI > 0.10$ by using Individual Conditional Expectation (ICE) plots [134], using the R-package *iml* [135]. These plots make it possible to visualize the relationship between a predictor and the predicted outcome for individual cases [136]. Following Goldstein et al. [136], let $\hat{f}(\chi)$ denote the estimated prediction function, with χ_s representing the predictor of interest and χ_c representing all other examined predictors. For each observation ι an individual ICE curve is defined as $\hat{f}_s^{(\iota)}(\chi_s) = \hat{f}\left(\chi_s, \chi_c^{(\iota)}\right)$ [134,136]. This means that the predictor of interest χ_s is systematically varied across its observed range, while all other predictors $\chi_c^{(\iota)}$ are held constant at their observed values for the respective student. This results in one curve per student, each representing the conditional relationship between the examined predictor and the predicted outcome [136]. The direction and strength of this association can be inferred from the slope of the individual curves, corresponding to the partial derivative $\frac{\partial \hat{f}\left(\chi_s, \chi_c^{(\iota)}\right)}{\partial \chi_s}$ [134,136]. Accordingly, a consistently positive or negative slope indicates a positive or negative association between the predictor and the outcome. In the plots, each line represents a student's hypothetical prediction across the value range of the examined predictor, which is shown on the *X*-axis. The *Y*-axis shows the predicted likelihood that the examined aspect was mentioned by the respective student, while all other predictors are held constant. The distribution of the examined predictor is shown along the *X*-axis.

The predictor variables were calculated as the mean score of the items of the respective scale. Beforehand, the psychometric properties of each scale were evaluated using confirmatory factor analysis (CFA). All CFA models indicated acceptable to good fit ($0.918 \leq$ CFI ≤ 0.963; $0.060 \leq$ RMSEA ≤ 0.087; $0.033 \leq$ SRMR ≤ 0.050) [137]. Cases with missing values on the predictors were excluded, resulting in the exclusion of $n = 22$ cases (3.2% of the sample).

5. Results

5.1. Positively Perceived Aspects of Distance Learning

Figure 1 shows the frequencies of aspects mentioned by students in response to the question, "*What did you like about distance learning? What do you think could stay the same?*"

The most frequently mentioned positive category concerned *advantages of being at home* ($n = 268$, e.g., 3229: "*I liked being at home. I don't like being at school because it is a place of stress and pressure for me.*" [Note: Since the data was collected in German, the quotes were translated into English]). Within this code, the students particularly emphasized the possibility to sleep longer ($n = 188$, e.g., 4060: "*That I could sleep in until the last moment*") and to wear comfortable clothes without dressing up ($n = 26$, e.g., 4623: "*You didn't have to 'dress up' much because you were without a camera anyway*").

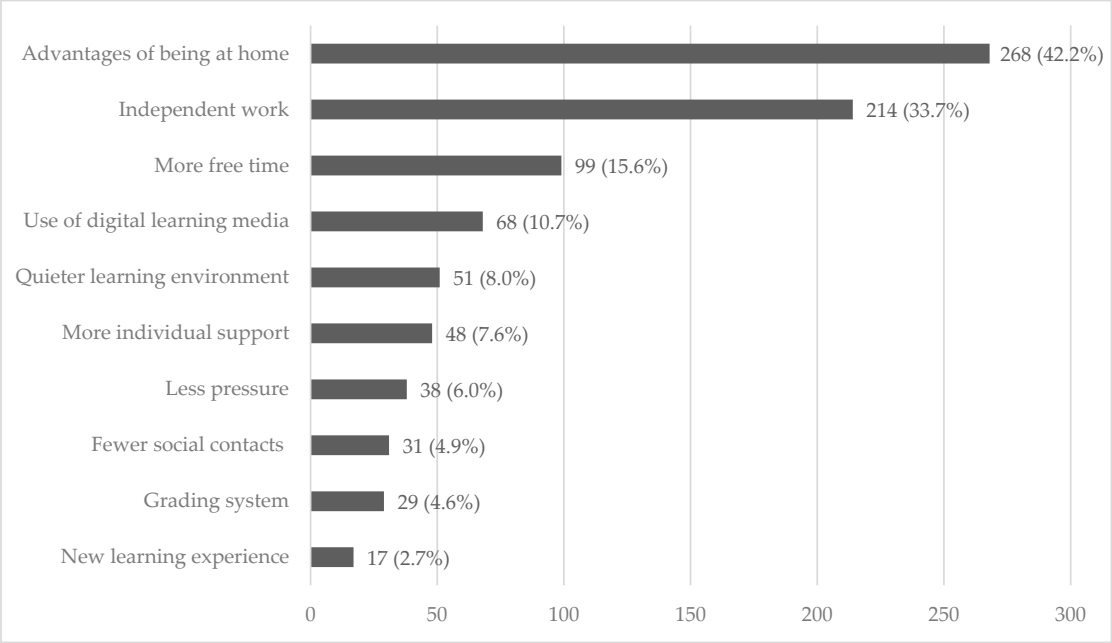


Figure 1. Frequency of positive aspects mentioned by students. Note: Percentages represent the number of students who noted certain aspects in relation to the total sample of students who answered this question. Due to the open-ended questions and the qualitative nature of the data, this does not necessarily represent the proportion of students who perceived these aspects positively.

The second most frequently mentioned positive aspect was the *opportunity to work independently and flexibly* (n = 214, e.g., 4557: "*That you can organize your own time, [decide] when you work on which tasks*"). The third most frequent response was having *more free time* (n = 99, e.g., 2008: "*I was able to do the tasks that the teacher gave us in the morning and then I was done. After that I could do other things.*").

Students also positively perceived the increased *use of digital learning media* (n = 68, e.g., 3025: "*I also liked the fact that the apps [Moodle in my case] were introduced. It gave me a much better overview.*") as well as an improved focus due to fewer distractions in a *quieter learning environment* (n = 51, e.g., 3063: "*I was able to concentrate better than at school because it wasn't so loud.*").

Additionally, some students perceived more *individualized support* (n = 48, e.g., 4254: "*That you can ask the teacher specific questions privately via an online portal theoretically at any time.*"), *reduced performance pressure* (n = 38, e.g., 3071: "*There was no pressure and you could learn without stress.*") and *less social interaction* as beneficial aspects (n = 31, e.g., 4048: "*I personally liked distance learning because I'm a bit of an introvert myself, so I don't have much to do with other people*"). Others appreciated the different grading system and received *better grades* (n = 29, e.g., 1063: "*No presentations and participation grades as a great relief for shy students*") or described distance learning as an enjoyable *new experience* (n = 17, e.g., 4097: "*It was just something different. I just like doing new things.*").

5.2. Negatively Perceived Aspects of Distance Learning

Figure 2 shows the frequencies of aspects mentioned by students in response to the question, "*What did you not like about distance learning?*".

The most frequently mentioned negative aspect was the *lack of social contacts* (n = 212, e.g., 2764: "*There was a lack of contact with friends and classmates [. . .]*"). This was followed by the *lack of direct learning support* and difficulty asking questions (n = 165, e.g., 2321: "*Sometimes you could hardly get any help from the teachers because you were on your own*"). Some students also reported a *higher workload* than in face-to-face learning (n = 87, e.g., 3905:

"*We were always given so much to do. As soon as one task was finished, another one followed immediately [. . .]*").

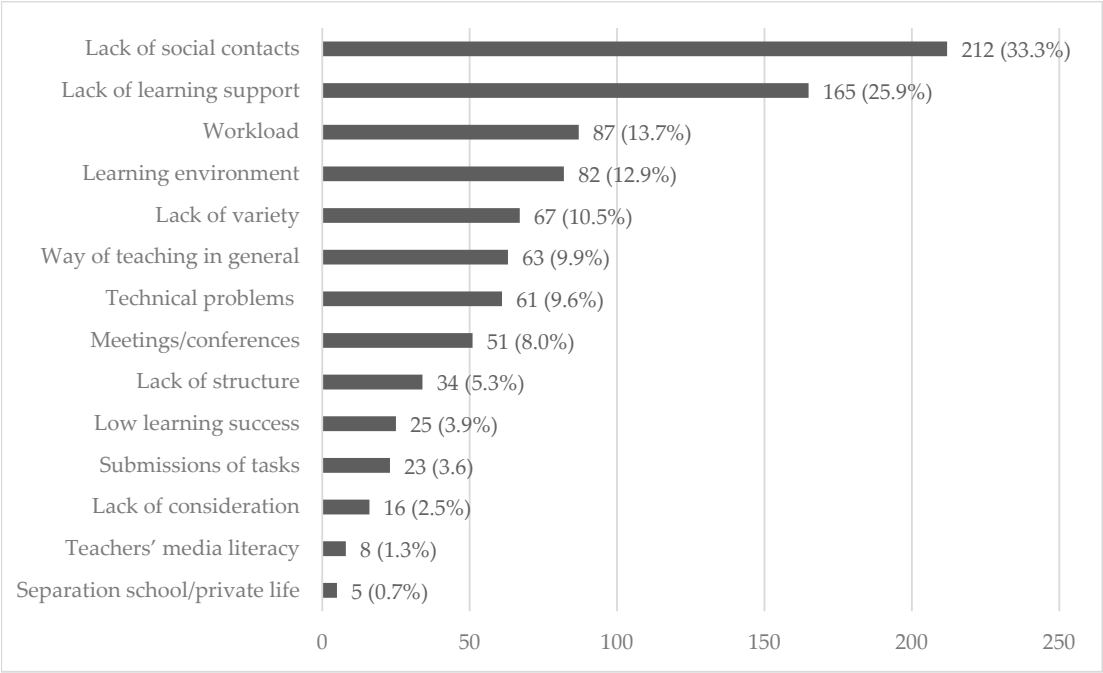


Figure 2. Frequency of negative aspects mentioned by students. Note: Percentages represent the number of students who noted certain aspects in relation to the total sample of students who answered this question. Due to the open-ended questions and the qualitative nature of the data, this does not necessarily represent the proportion of students who perceived these aspects negatively.

The home learning environment was perceived as problematic by some, due to *distractions or low motivation* (n = 82, e.g., 1033: "*Lack of concentration because I didn't have a quiet place*"). Additional negative aspects included the *lack of variety* (n = 67), specifically the restricted ability to leave the house (n = 28, e.g., 2971: "*That you weren't allowed to leave the house [. . .]*"), and excessive screen time (n = 21, e.g., 2301: "*That you had to stare at a screen so much and that strained your eyes [. . .]*").

Further, students also criticized the *general quality of lessons and tasks* (n = 63, e.g., 957: "*There were no online lessons. Everything was just on paper; tasks were distributed, and you had to solve and upload via a cloud.*") and reported *technical issues* (n = 61, e.g., 2875: "*The program crashed for many [students]—class was often interrupted as a result.*").

Video conferencing was viewed negatively by some (n = 51), who criticized irregular usage (e.g., 964: "*Only a few teachers used digital services such as video conferencing, so no exchange was possible*") or discomfort with showing their home environment (e.g., 3185: "*Having to turn on the camera is more uncomfortable than sitting in class*"). A *lack of structure* in lessons and school organization was also noted (n = 34, e.g., 1094: *"[. . .] at my school, the whole thing seemed very unstructured to me.*").

Other negatively perceived aspects included *lower learning success* (n = 25, e.g., 4608: "*You learned less. Especially in the next school year, when face-to-face lessons took place again, there were many gaps in subjects such as math and physics.*"), short *deadlines for assignments* (n = 23, e.g., 2417: "*Many deadlines had to be met that don't normally exist [. . .]*"), *lack of consideration* from teachers (n = 16, e.g., 1087: *"[. . .] and no consideration was given to the fact that it was also a difficult time for us.*"), low *digital competence among teachers* (n = 8, e.g., 3077: "*Unfortunately, some teachers were also technically untalented [. . .]*"), and a *blurred boundary between school and*

private life (n = 5, e.g., 2398: "*You could no longer switch off [. . .] school and free time were no longer two separate things [. . .]*").

5.3. Descriptive Analysis of the Considered Predictors

The mean values, standard deviations, skewness, and kurtosis of the predictors included in the random forest models, as well as the correlations between them are reported in Table A2 in Appendix A.

5.4. Predictors of Positively Perceived Aspects

Table 2 shows the *MSE*, *AUC*, and *Gini* coefficient of the random forest models predicting the occurrence of positively mentioned aspects. Taken together, these fit indices indicate good model performance [138]. Table 3 displays the *VI* and *%VI* of each predictor examined.

Table 2. Fit indices of the random forest models regarding the positively mentioned aspects.

Criterion	Advantages of Being at Home	Independent Work	More Free Time	Use of Digital Learning Media	Quieter Learning Environment
MSE	0.167	0.182	0.122	0.177	0.127
AUC	0.914	0.908	0.936	0.903	0.925
Gini	0.829	0.815	0.872	0.805	0.849

Table 3. Relative importance and percentage contribution to total variable importance of each examined predictor in the random forest models to predict the positively mentioned aspects.

Predictors	Advantages of Being at Home		Independent Work		More Free Time		Use of Digital Learning Media		Quieter Learning Environment	
	VI	*%VI*	*VI*	*%VI*	*VI*	*%VI*	*VI*	*%VI*	*VI*	*%VI*
Gender	1403.6	0.095	2172.8	0.066	**2447.4**	**0.131**	1307.0	0.075	421.3	0.036
Age	**1658.2**	**0.112**	**5017.6**	**0.153**	650.0	0.035	1635.3	0.093	893.4	0.077
Country of schooling	**1502.8**	**0.101**	**4982.5**	**0.152**	**8253.1**	**0.442**	**3870.1**	**0.221**	**1381.3**	**0.119**
First language	1152.4	0.078	**5600.2**	**0.170**	1798.3	0.096	1617.8	0.092	746.4	0.064
Self-regulation	**1547.6**	**0.104**	2366.9	0.072	767.1	0.041	1295.5	0.074	858.5	0.074
Procrastination	**1673.8**	**0.113**	3036.3	0.092	574.2	0.031	913.7	0.052	**3364.7**	**0.291**
Self-assessed learning success	1431.5	0.096	2756.9	0.084	**2223.4**	**0.119**	**2050.1**	**0.117**	**1376.7**	**0.119**
Equipped workspace	**1585.1**	**0.107**	1506.8	0.046	483.8	0.026	1134.5	0.065	518.7	0.045
Equipped household	1442.4	0.097	1496.6	0.046	766.5	0.041	1359.3	0.078	927.0	0.080
Number of books	1444.3	0.097	**3924.3**	**0.119**	706.5	0.038	**2355.5**	**0.134**	1091.9	0.094

Predictor values with *%VI* > 0.1 printed in bold.

Advantages of being at home were slightly more likely to be mentioned by students who reported higher levels of *procrastination*, although the probability decreased among students who *procrastinated* very frequently (*%VI* = 0.113, Figure 3a). Furthermore, students with lower levels of *self-regulation* were also more likely to mention this aspect (*%VI* = 0.104, Figure 3b). Sensitivity analyses excluding cases with particularly low self-regulation scores (self-regulation < 1.5) confirmed the robustness of this pattern: *self-regulation* remained a relevant predictor, and students with lower levels of self-regulation continued to be more likely to mention this aspect. Likewise, *younger students* (*%VI* = 0.112, Figure 3c) and those with *better-equipped home workspaces* (*%VI* = 0.107, Figure 3d) were also more likely to refer to this aspect.

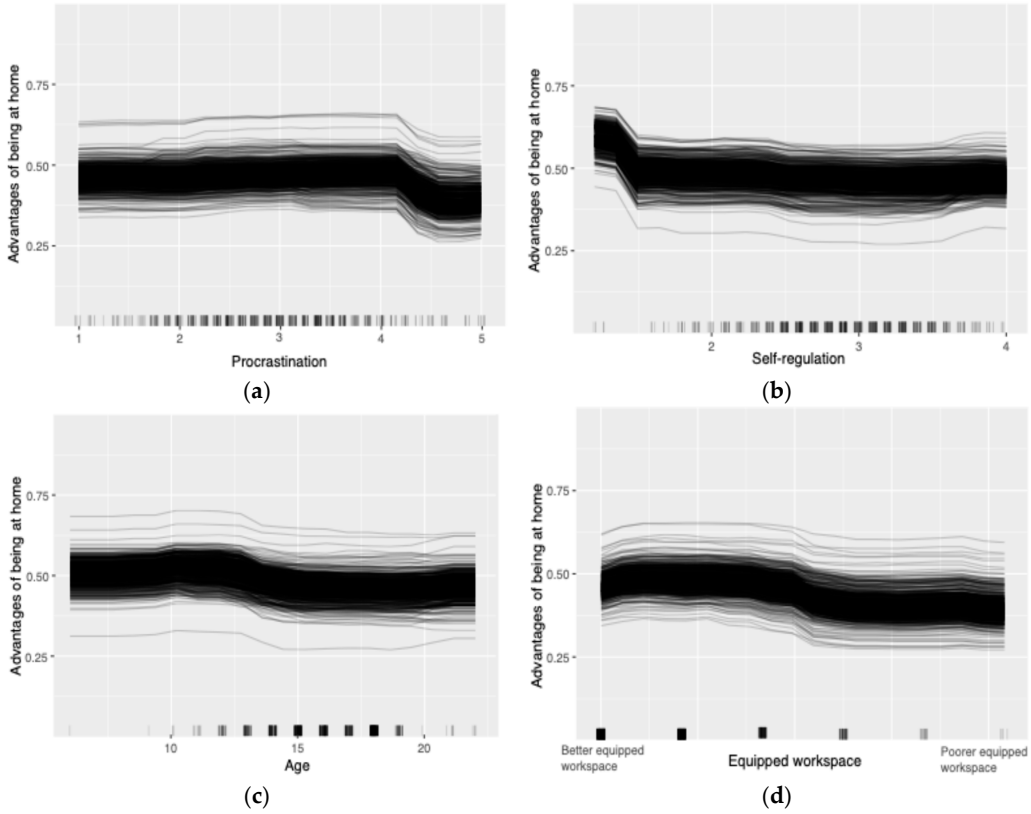


Figure 3. *ICE Plot* showing the conditional relationship between the frequency of *procrastination* (**a**), self-assessed *self-regulation* (**b**), students' *age* (**c**) and *equipped home workspace* (**d**) on the likelihood of students mentioning the *advantages of being at home* as a positive aspect. Likelihood of mentioning *advantages of being at home* shown on the *Y*-axis.

Independent and flexible work was most often predicted by *first language* (%*VI* = 0.170), with students who spoke German being more likely to mention this aspect (Figure 4a). *Age* also emerged as a predictor (%*VI* = 0.153): students aged 13–19 were most likely to mention this aspect, although the likelihood declined among older students (Figure 4b). In addition, students from *Switzerland* (%*VI* = 0.152, Figure 4c) were more likely to mention this aspect. The *number of books* in students' households was also identified as a predictor (%*VI* = 0.120). However, no consistent trend was observed here, except that students with a very low number of books at home, and to a lesser extent those with a very high number of books, were less likely to highlight this advantage (Figure 4d).

Country of schooling emerged as an important predictor of students mentioning *more free time* as a positive effect (%*VI* = 0.442), with students from Switzerland more likely to mention this aspect (Figure 5a). *Male students* (%*VI* = 0.131, Figure 5b) and students with lower *self-assessed learning success* (%*VI* = 0.120, Figure 5c) were also more likely to report this aspect.

Increased use of digital learning media was more frequently mentioned by students from *Germany* (%*VI* = 0.221, Figure 6a) and by students from *households with a higher number of books* (%*VI* = 0.134, Figure 6b). Furthermore, students who rated their *learning success* as lower were more likely to mention this aspect (%*VI* = 0.117, Figure 6c).

The mention of a quieter learning environment was most often predicted by lower levels of *procrastination* (%*VI* = 0.291, Figure 7a). In addition, this aspect was more frequently mentioned by students from *Germany* (%*VI* = 0.119, Figure 7b) and by those who rated their *learning success* more positively (%*VI* = 0.119, Figure 7c).

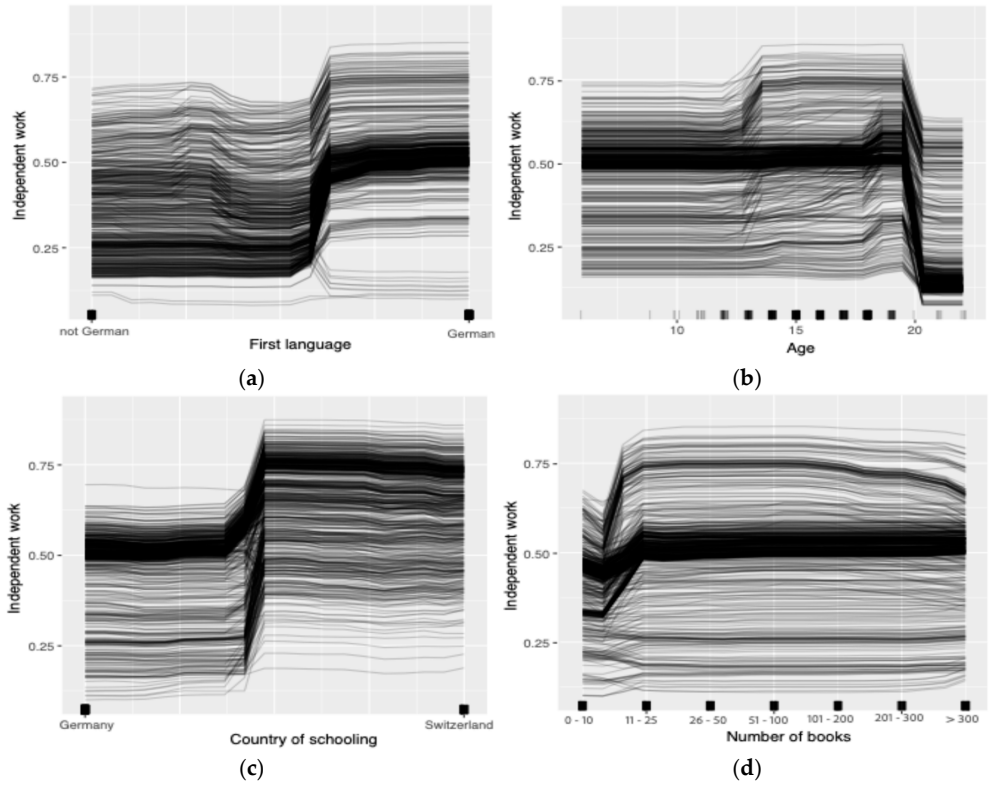


Figure 4. *ICE Plot* showing the conditional relationship between students' *first language* (**a**), *age* (**b**), *country of schooling* (**c**) and the *number of books in students' households* (**d**) on the likelihood of students mentioning the *higher amount of independent work* as a positive aspect. Likelihood of mentioning *independent work* shown on the *Y*-axis.

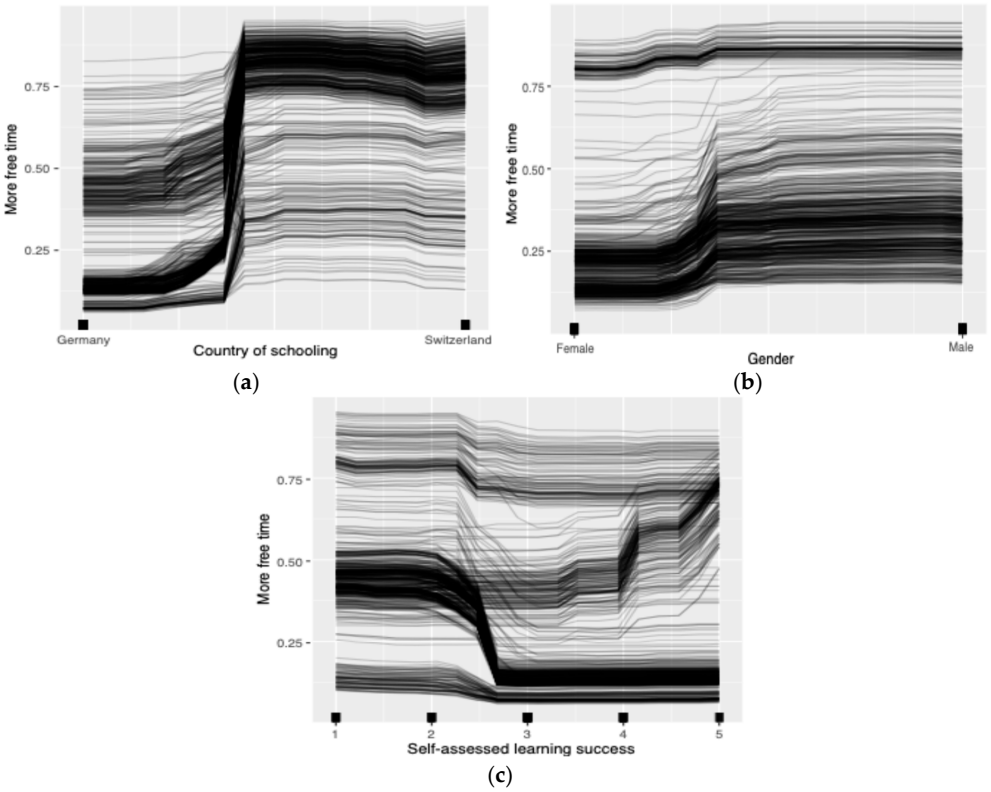


Figure 5. *ICE Plot* showing the conditional relationship between the *country of schooling* (**a**), student *gender* (**b**), and *self-assessed learning success* (**c**) on the likelihood of students mentioning *more free time* as a positive aspect. Likelihood of mentioning *more free time* shown on the *Y*-axis.

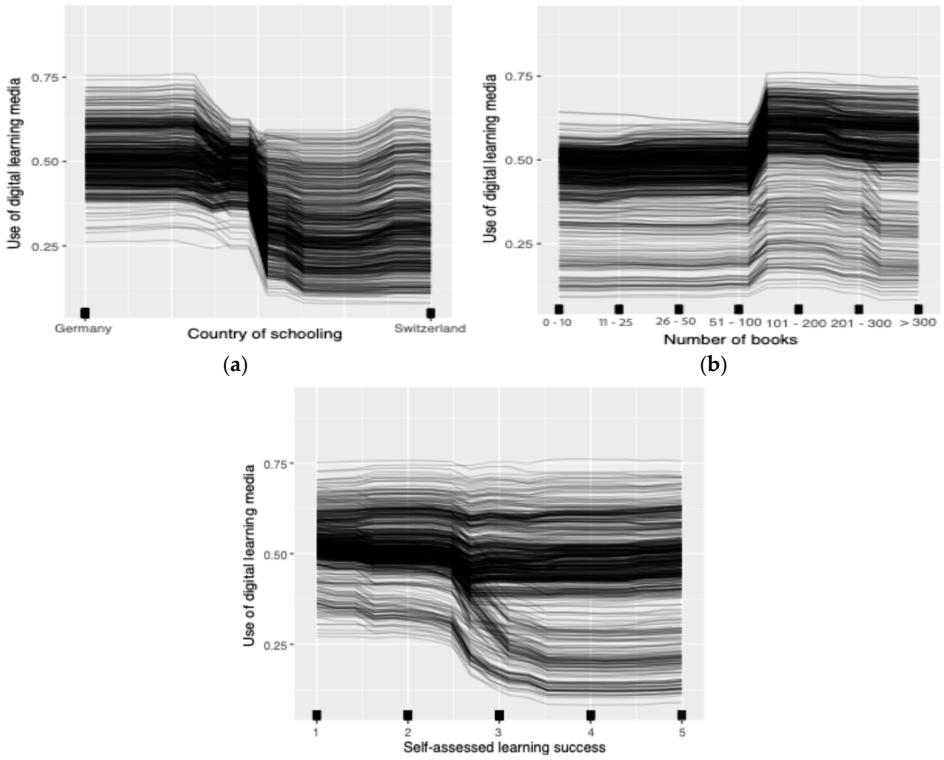


Figure 6. *ICE Plot* showing the conditional relationship between the *country of schooling* (**a**), the *number of books in students' households* (**b**), *and the self-assessed learning success* (**c**) on the likelihood of students mentioning the higher *use of digital learning media* as a positive aspect. Likelihood of mentioning *use of digital learning media* shown on the *Y*-axis.

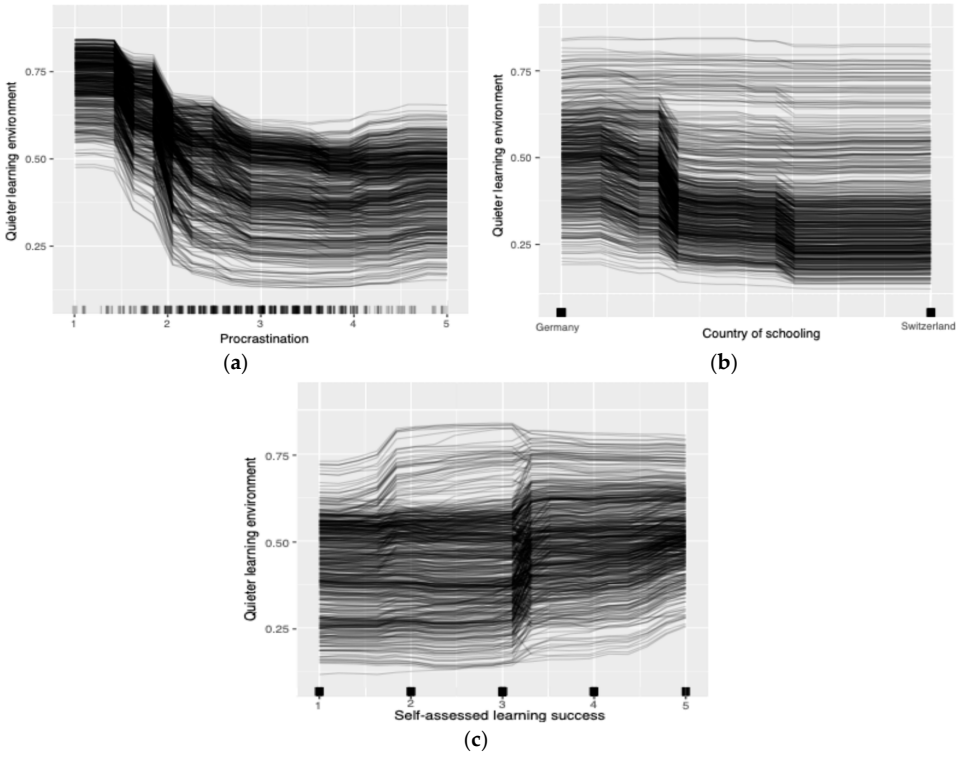


Figure 7. *ICE Plot* showing the conditional relationship between the *frequency of procrastination* (**a**), the *country of schooling* (**b**), *and the self-assessed learning success* (**c**) on the likelihood of students mentioning the *quieter learning environment* at home as a positive aspect. Likelihood of mentioning *quieter learning environment* shown on the *Y*-axis.

5.5. Predictors of Negatively Perceived Aspects

Table 4 shows the *MSE*, *AUC*, and *Gini* coefficient of the calculated random forest models. Taken together, these fit indices indicate good model performance [138]. Table 5 presents the *VI* and *%VI* of each predictor variable.

Table 4. Fit indices of the random forest models regarding the negatively mentioned aspects.

Criterion	Lack of Social Contacts	Lack of Learning Support	Workload	Learning Environment	Lack of Variety
MSE	0.172	0.207	0.171	0.175	0.181
AUC	0.922	0.940	0.923	0.898	0.882
Gini	0.845	0.881	0.847	0.797	0.764

Table 5. Relative importance and percentage contribution to total variable importance of each examined predictor of the random forest models to predict the negatively mentioned aspects.

Predictors	Lack of Social Contacts		Lack of Learning Support		Workload		Learning Environment		Lack of Variety	
	VI	*%VI*	*VI*	*%VI*	*VI*	*%VI*	*VI*	*%VI*	*VI*	*%VI*
Gender	1184.7	0.061	**1251.3**	**0.124**	**2560.2**	**0.148**	404.9	0.072	946.5	0.048
Age	**2774.3**	**0.142**	**1101.5**	**0.109**	1628.9	0.094	361.3	0.064	1076.8	0.055
Country of schooling	**2882.2**	**0.148**	889.8	0.089	986.7	0.057	**795.5**	**0.141**	1767.2	0.090
First language	**3025.8**	**0.155**	823.3	0.082	**2031.0**	**0.118**	496.4	0.088	956.3	0.049
Self-regulation	1284.4	0.066	**1022.1**	**0.102**	**2095.4**	**0.121**	456.5	0.081	**3353.9**	**0.171**
Procrastination	1727.4	0.088	**1026.7**	**0.102**	1596.2	0.093	**808.7**	**0.143**	**3457.9**	**0.176**
Self-assessed learning success	1355.5	0.069	965.2	0.096	1133.3	0.066	**970.1**	**0.172**	1801.5	0.092
Equipped workspace	1549.6	0.079	987.7	0.098	1702.1	0.099	**605.8**	**0.107**	**2273.7**	**0.116**
Equipped household	**2007.8**	**0.103**	981.6	0.098	1300.8	0.075	362.8	0.064	**2261.5**	**0.115**
Number of books	1744.2	0.089	**1015.4**	**0.101**	**2216.9**	**0.129**	376.1	0.067	1751.2	0.089

Predictor values with *%VI* > 0.1 printed in bold.

The *lack of social contact* was more frequently mentioned by students whose *first language* was German (*%VI* = 0.155, Figure 8a), students from *Switzerland* (*%VI* = 0.148, Figure 8b), *younger students* (*%VI* = 0.142, Figure 8c), and those from *better-equipped households* (*%VI* = 0.103, Figure 8d).

Regarding the *lack of learning support*, students' *gender* emerged as an important predictor (*%VI* = 0.124). The results indicated a slight tendency for *female* students to mention this aspect more frequently (Figure 9a). In addition, students in *elementary* and *upper secondary school* were more likely to refer to this aspect than students in lower secondary school (*%VI* = 0.109, Figure 9b). Furthermore, students who reported lower levels of *procrastination* (*%VI* = 0.102, Figure 9c) and those who rated their *self-regulation* more highly (*%VI* = 0.102, Figure 9d) were also more likely to mention this aspect.

High workload was more frequently mentioned by *female students* (*%VI* = 0.148, Figure 10a). In addition, students from households with a *low number of books* were more likely to mention this aspect, although a slight opposite tendency was observed for some students (*%VI* = 0.129, Figure 10b). Furthermore, students with higher levels of *self-regulation* (*%VI* = 0.121, Figure 10c), and students whose *first language* was *not German* (*%VI* = 0.118, Figure 10d) were also more likely to report this issue.

Lower motivation or concentration in the home environment was more likely to be mentioned by students who rated their *learning success* as lower (*%VI* = 0.172, Figure 11a), those who reported higher levels of *procrastination* (*%VI* = 0.143, Figure 11b), and students from *Germany* (*%VI* = 0.141, Figure 11c). Counterintuitively, students with *better-equipped workspaces* were also more likely to report this issue (*%VI* = 0.107, Figure 11d).

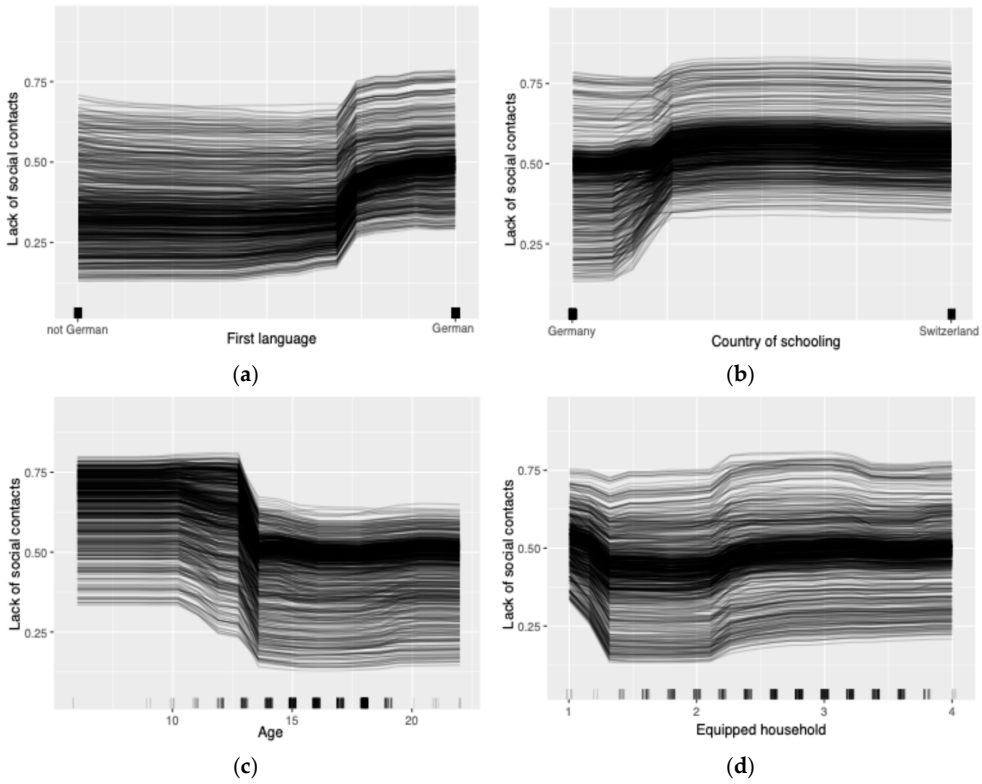


Figure 8. *ICE Plot* showing the conditional relationship between students' *first language* (**a**), the *country of schooling* (**b**), students' *age* (**c**) and students' *equipped household* (**d**) on the likelihood of students mentioning the *lack of social contacts* as a negative aspect. Likelihood of mentioning *lack of social contacts* shown on the *Y*-axis.

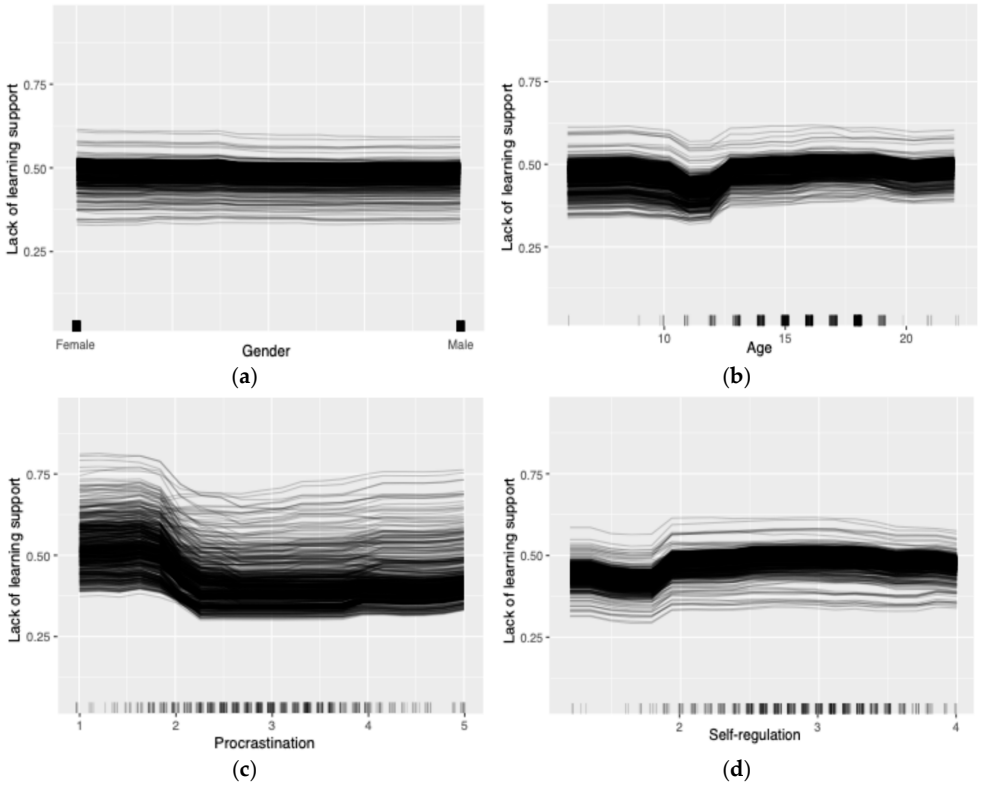


Figure 9. *ICE Plot* showing the conditional relationship between student *gender* (**a**), age (**b**), frequency of *procrastination* (**c**) and *self-regulation* (**d**) on the likelihood of students mentioning the *lack of learning support* as a negative aspect. Likelihood of mentioning *lack of learning support* shown on the *Y*-axis.

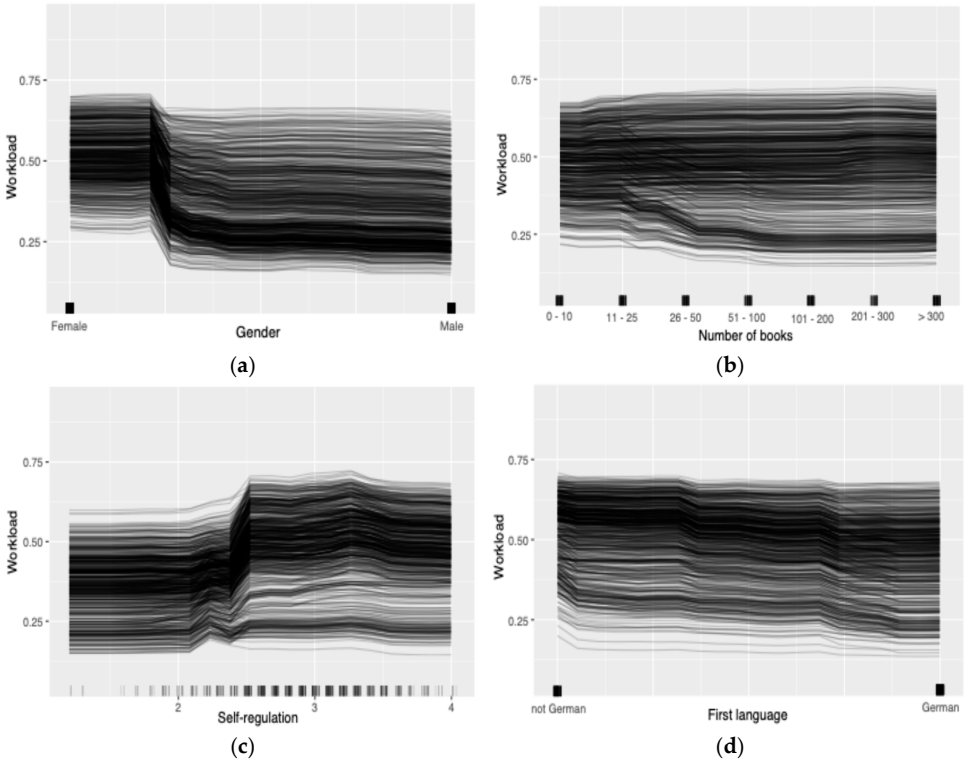


Figure 10. *ICE Plot* showing the conditional relationship between students' *gender* (**a**), *number of books* in students' households (**b**), self-assessed *self-regulation* (**c**) and students' *first language* (**d**) on the likelihood of students mentioning the *higher workload* as a negative aspect. Likelihood of mentioning *higher workload* shown on the *Y*-axis.

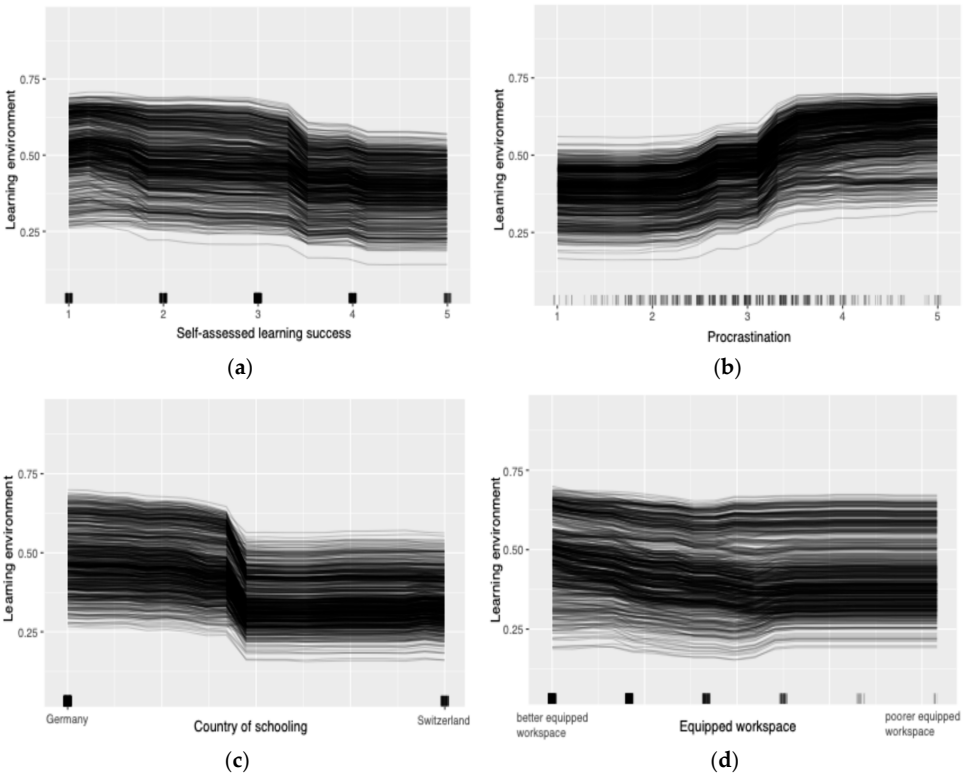


Figure 11. *ICE Plot* showing the conditional relationship between *self-assessed learning success* (**a**), frequency of *procrastination* (**b**), *country of schooling* (**c**) and *equipped workspace* (**d**) on the likelihood of students mentioning the *home learning environment* as a negative aspect. Likelihood of mentioning *home learning environment* shown on the *Y*-axis.

A *lack of variety* was more frequently reported by students who indicated lower levels of *procrastination* (%*VI* = 0.176, Figure 12a) and higher *self-regulation* (%*VI* = 0.171, Figure 12b). Students from less well-equipped households (*workspace equipment*: %*VI* = 0.116, *household equipment*: %*VI* = 0.115, Figure 12c,d) were also more likely to mention this aspect.

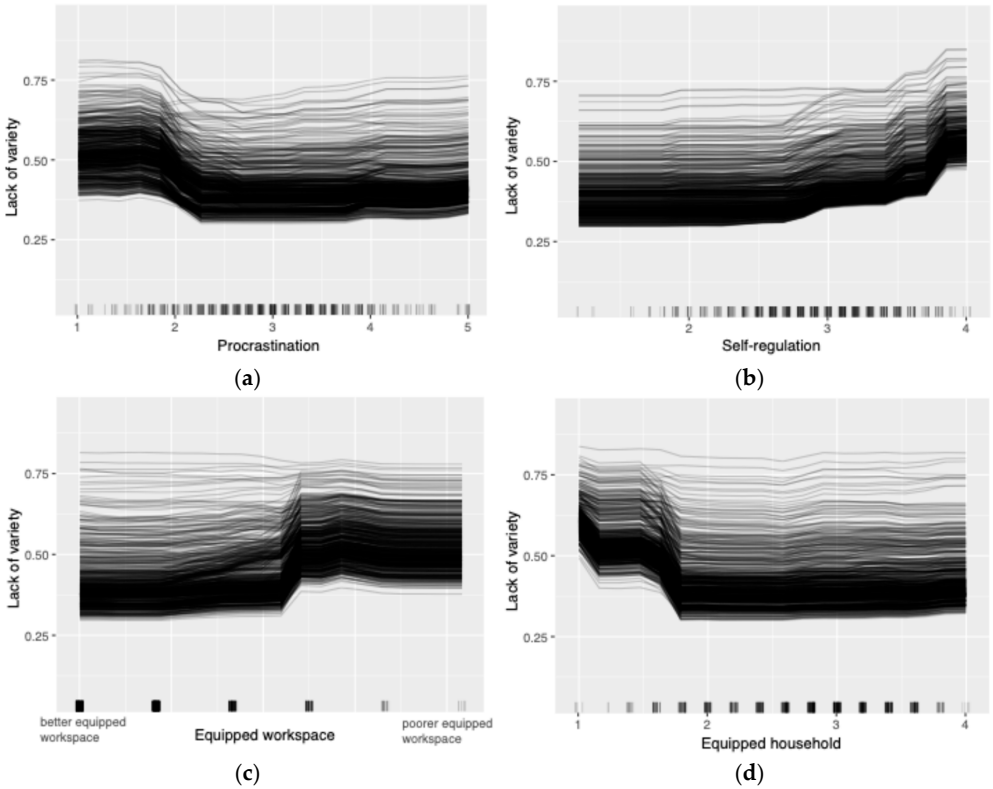


Figure 12. *ICE Plot* showing the conditional relationship between *frequency of procrastination* (**a**), self-assessed *self-regulation* (**b**), *equipped workspace* (**c**) and *household* (**d**) on the likelihood of students mentioning the *lack of variety* as a negative aspect. Likelihood of mentioning *lack of variety* shown on the *Y*-axis.

6. Discussion

School closures during the COVID-19 pandemic substantially altered students' everyday school lives and affected both their learning and their well-being [4,139]. However, as well-being is a highly subjective, multi-source phenomenon [7], these effects on students' well-being cannot be fully captured by global well-being indicators alone. In line with Diener's definition [9] and the related bottom-up theory [10], well-being is shaped by the accumulation of positively and negatively perceived experiences and emotions. Accordingly, by examining which aspects of distance learning students perceived positively and negatively, the present study provides a more differentiated, experience-based perspective on how school closures affected students' well-being during the pandemic. [8,21–23].

At the same time, these perceptions varied considerably across students. This heterogeneity is consistent with multidimensional models of student well-being, which emphasize that school-related well-being emerges from the interplay of individual characteristics, contextual conditions, and broader background factors [12,18–20]. To discuss these patterns at a broader interpretive level, the aspects mentioned by students were grouped into overarching thematic domains. The following discussion is structured around these domains and examines how the identified predictors shaped whether specific aspects of distance learning were perceived positively or negatively.

6.1. Home Learning Environment

In the present study, the most frequently mentioned positive aspect was the advantage of being at home. Many students perceived learning from home as more pleasant than attending school. Students with stronger tendencies to procrastinate or lower levels of self-regulation were more likely to mention this aspect. This may reflect a reduced sense of pressure outside the formal school setting, potentially creating a critical combination that could further decrease engagement with school and learning activities [140]. It might be meaningful to pay particular attention to ensure that these students remain supported and actively engaged during distance learning. Younger students were also more likely to value being at home. This pattern may be related to several factors. First, the home environment represents a particularly influential social context for younger students [141,142]. Second, younger students often benefited more from parental support, while the absence of peer-based social comparison played a less significant role for them [143–145]. Similarly, students with well-equipped home workspaces were more likely to report this aspect positively, possibly because they tended to have access to quiet, undisturbed learning environments. In contrast, students in less favorable home environments may have faced more interruptions during learning from home. Moreover, students with better-equipped workspaces may generally have experienced a more comfortable learning environment, which could further increase their preference for learning at home.

As one of the advantages of being at home, many students also described the opportunity to sleep longer as a positive aspect. This observation aligns with prior research indicating that conventional school start times are often misaligned with adolescents' biological rhythms [146,147], thereby reinforcing arguments in favor of delaying school start times under regular conditions in order to enhance students' well-being and academic outcomes [148].

Moreover, the finding that many students experienced learning from home as more pleasant than attending school is consistent with the frequent mention of reduced perceived pressure as a positive aspect of distance learning. This pattern may suggest that, for many students, the traditional school environment is associated with heightened performance-related pressure [149,150]. In this context, distance learning may have temporarily alleviated these strains by reducing such negative associations.

Beyond that, some students reported fewer distractions while learning at home as a benefit, whereas others experienced greater difficulties with concentration and motivation. Students who procrastinated less frequently and reported higher learning success tended to view their home learning environment more positively. In contrast, students who procrastinated more often or reported lower self-assessed learning success were more likely to perceive their environment negatively. These findings indicate the importance of self-regulation for overcoming procrastination and successfully managing distance learning. For students who struggle to maintain focus and motivation at home, providing access to on-site learning opportunities during periods of distance learning may therefore be beneficial.

In the present study, students from Germany were more likely to report challenges related to their home learning environment than students from Switzerland. This country difference may point to contextual differences in how distance learning was experienced rather than to a direct country effect. Several tentative explanations may be considered. First, the longer duration of restrictions in Germany may have contributed to greater fatigue among students [87,88]. Second, differences in the preparedness of the school systems for digitally supported distance learning may also be relevant. At the beginning of the pandemic, the German school system appeared to face greater challenges in implementing digitally supported distance learning than the Swiss system, as reflected, for example, in frequent server overloads on learning platforms [31,54]. Switzerland, by contrast, may have been comparatively better positioned for digitally supported teaching at the onset of the

pandemic, possibly partly due to higher investment in education per student [54,151]. This could have supported the implementation of distance learning through more stable school networks and greater availability of digital devices, which may in turn have facilitated independent learning [152]. However, these interpretations remain tentative and should be examined more directly in future research. In addition, students with less well-equipped home workspaces were more likely to mention negative aspects of distance learning in this regard, possibly due to noise, distractions, or the lack of a dedicated learning space.

In many cases, the home learning environment can therefore provide a protective and supportive framework for learning. However, for some students—particularly those with limited home learning resources or weaker self-regulation skills—it may also pose risks. Within the integrative model of student well-being, this pattern indicates that students' appraisals of the home learning environment were shaped by the interplay of contextual conditions and intrapersonal characteristics. In the present study, individual learning behavior appeared to be particularly relevant in this regard. Where limited environmental resources coincided with weaker self-regulatory capacities, the home learning environment was more likely to be experienced as challenging rather than supportive. This constellation may, in turn, contribute to reduced learning engagement, limited learning progress, and increased stress [13,153].

6.2. Independent and Flexible Work

The second most frequently mentioned positive aspect in our analyses was the opportunity to work independently and flexibly. This finding aligns with prior research highlighting the motivational benefits of increased autonomy while learning [154,155]. Students with higher language proficiency—those who spoke German as their first language—were more likely to report this aspect positively. Possibly, these students may have found it easier to understand written instructions, whereas students with less language experience may have faced greater difficulties in this regard. Furthermore, parents with a migration background may have faced additional challenges in supporting their children during distance learning, potentially due to language barriers and limited familiarity with the school system [156,157]. These results indicate the importance of language skills for autonomous learning and suggest that students with limited language proficiency may require additional scaffolding during distance learning phases [49].

In the current study, secondary school students (aged 13–19) were also more likely to view independent work positively compared to primary school students as well as students aged 20 and above. As self-regulation skills develop with age [158], younger students may struggle more often with autonomous learning and require closer guidance. This pattern may also be reflected in the more frequent mention of a lack of direct learning support among younger students. However, among older students, the likelihood of reporting independent work positively also declined. One possible interpretation is that students aged 20 years and above who are still enrolled in school may face specific challenges in self-regulated learning, which could make independent work in distance learning more difficult for them.

Students from Switzerland, who experienced shorter school closures, were more likely to rate independent work positively in our analyses. This pattern may suggest that more limited exposure to prolonged distance learning was associated with more favorable perceptions of independent work. One possible interpretation is that, for these students, distance learning may have retained a greater sense of novelty and may therefore have been perceived as less burdensome. This is consistent with previous studies indicating that some students initially reported higher motivation at the beginning of distance learning, whereas motivation declined substantially as school closures continued over longer periods [89,159]. However, the present data do not allow us to determine whether duration of exposure directly accounted for this country difference.

Students from families with lower cultural capital were less likely to report positive perceptions of independent work. Parents with higher educational attainment are generally better able to support their children's independent learning [52]. Teachers may therefore consider the expected level of support available in students' home environments and provide additional assistance to those who lack such support during future distance learning phases.

While many students valued independent work in our analyses, others reported missing direct learning support. In the present study, female students reported a lack of learning support slightly more often. This pattern may be interpreted in light of previous findings indicating that female students tend to report higher academic expectations or greater conscientiousness [42]. As a result, they may have been more sensitive to insufficient guidance or limited opportunities for clarification during distance learning. Male students, by contrast, often show higher levels of self-efficacy [160] which may have supported them in managing independent tasks with less perceived need for direct learning support.

In addition to elementary school students, upper secondary school students also reported a lack of direct learning support. Despite their more developed self-regulation skills [158], they may have perceived the complex curriculum as overwhelming, which may have hindered independent learning [161]. Students with higher self-regulation skills and those who procrastinated less frequently were more likely to report missing direct learning support. This pattern may indicate that some students attempted to engage conscientiously with schoolwork during distance learning but nevertheless experienced difficulties in meeting their own learning expectations, possibly due to challenges in understanding the instructional content [162]. Teachers should therefore ensure that students have sufficient opportunities to ask questions and clarify misunderstandings during distance learning [163]. The frequent mention of increased individual support as a positive aspect may suggest that some teachers were already able to implement such practices effectively during the COVID-19 pandemic. This variation also highlights that the quality and structure of distance learning differed considerably between classrooms, depending on how instruction was organized and the extent to which opportunities for individualized interaction were provided [164].

Independent work offers opportunities for autonomy but also carries the risk of disengagement among students who lack the skills to self-direct their learning [165,166]. Interpreted within the integrative model of student well-being, differences in students' evaluations of independent work can be attributed primarily to demographic characteristics as part of broader background variables, as well as to students' individual learning behavior as part of their intrapersonal characteristics. This pattern underscores that the benefits of autonomy depend not only on the learning context but also on students' individual capacities to regulate their learning. Accordingly, these findings highlight the importance of fostering self-regulatory strategies under normal conditions [167], as these skills remain relevant beyond students' time in school [168]. At the same time, these findings indicate the need to balance autonomy with structure. For example, teachers could provide structured learning dossiers with a set of tasks while allowing students autonomy regarding the pace and order in which they complete the tasks.

6.3. Workload

Another positively perceived aspect was having more free time during the period of distance learning. Students from Switzerland were more likely to mention this aspect. This difference may reflect the comparatively less restrictive lockdown measures in Switzerland, which could have allowed more opportunities for leisure activities. Such an interpretation is consistent with studies showing that individuals in countries with more restrictive containment measures tended to feel more constrained [169]. However, this explanation remains tentative, as the present analyses cannot determine whether differences in containment measures directly shaped students' perceptions of free time.

Male students also reported this aspect more frequently, possibly reflecting gender-related differences in time use or engagement styles [170]. Students who rated their learning success as lower were likewise more likely to mention having more free time, possibly suggesting that disengagement from academic tasks may have contributed to this perception. While flexibility can be beneficial, it may also lead to reduced engagement for some students, highlighting the importance of balancing autonomy with structured learning.

At the same time, some students reported an increased workload, despite findings that overall learning time declined during the pandemic [31,35]. This may reflect students' difficulties in managing independent tasks. Female students and students with higher self-regulation more frequently reported a higher workload, suggesting that a more conscientious approach to learning may increase the perceived workload [171]. Students with lower levels of cultural capital and those who spoke a language other than German as their first language were also more likely to report high workloads—possibly reflecting lower parental support, leading to higher difficulties during self-regulated learning. It might therefore be beneficial for teachers to provide additional guidance to these students to prevent overload.

Another factor that may have contributed to students' feelings of overload and to the perception of an increased workload is the loss of clear structure, which was frequently mentioned as a negative aspect by many students. Schools typically provide a structured environment that provides students with reliable routines [172]—an element that becomes particularly important under crisis conditions [71]. Accordingly, in teaching during crisis situations, it seems essential to maintain a clear and reliable structure, for example through an adapted timetable that reflects the specific constraints of the situation [173].

Overall, students' perceptions of time and workload during distance learning were divided. While some valued the increased flexibility and additional free time, others experienced an intensified workload due to conscientiousness, limited support, or self-regulatory strain. Interpreted within the integrative model of student well-being, these differences were not attributable to a single dominant factor but were instead distributed across multiple levels that contribute to students' well-being, including intrapersonal characteristics, contextual conditions, and broader background variables. This pattern indicates a high degree of heterogeneity in how these factors were associated with students' perceptions of workload as experience-based indicators of their well-being. Accordingly, these findings suggest that students may benefit from distance learning arrangements that combine autonomy with structured guidance. The design of learning tasks may be one important element in achieving such a balance (cf. Section 6.2).

6.4. Peer Contact and Relatedness

The most frequently mentioned negative aspect was the lack of social contact. Social interaction is central to students' well-being and serves as a buffer against psychological distress [67,68,72]. From the perspective of Self-Determination theory [69], the loss of relatedness undermines motivation and learning. In future distance learning situations, structured social interactions—such as collaborative group tasks or informal online meetings—should therefore be intentionally integrated [173,174]. Notably, students who speak German as their first language and younger students were more likely to mention the lack of social contact. The first finding is consistent with a study from Finland that also reported higher levels of loneliness among students without a migrant background compared to those with a migrant background [175]. However, it contrasts with the findings of Koo and Nyunt (2023) [83], who reported greater loneliness among students with a migrant background in U.S. universities. This discrepancy may reflect cultural or contextual differences. Immigrant families often exhibit stronger community cohesion, which could help maintain a sense of relatedness [175,176]. Students with a migrant background

may also be more accustomed to smaller or closer-knit social networks [177], potentially reducing their sensitivity to broader social restrictions. The second finding—that younger students more frequently reported missing social contact—contradicts Shah and Househ (2023), who found older students to be more affected by loneliness [81]. However, younger students may lack the skills or resources to maintain digital contact with peers [80], making them more vulnerable to isolation. As peer interactions are important for both social development and academic engagement [178], for younger students it might be helpful to receive additional support to maintain peer relationships during distance learning.

Students from Switzerland—despite experiencing shorter and less restrictive closures [87,88]—were also more likely to report missing social contact compared to students from Germany. One possible hypothesis is that students in Germany, having experienced restrictions for a longer period, may have become more accustomed to reduced social interaction over time, whereas students in Switzerland may have perceived the disruption of social contact as more salient. This interpretation would be consistent with a habituation perspective [179]. However, the present study cannot directly test such a habituation mechanism, and future research should examine more specifically how the duration and intensity of restrictions relate to students' perceptions of social contact.

In contrast, a smaller number of students perceived the reduced level of social interaction as beneficial. This may particularly apply to more introverted students, who may have experienced reduced pressure to participate in classroom settings, as well as to students who may have been less exposed to bullying during this period [180].

Overall, social isolation represents a major risk factor, particularly for younger students and those with limited digital social resources. Interpreted within the integrative model of student well-being, differences in the perceived effect of social contact were primarily associated with sociodemographic characteristics and thus with students' broader background variables. This pattern suggests that vulnerabilities to social isolation during distance learning are strongly shaped by students' developmental stage and social context. Distance learning designs should therefore intentionally incorporate structured social interactions (e.g., collaborative group tasks, informal online meetings) to sustain relatedness and support both socio-emotional and academic outcomes [102,103,105].

6.5. Digital Media and Instructional Variety

Some students perceived the increased use of digital media as a positive aspect of distance learning. While digitalization was already relatively advanced in Switzerland [54], the shift toward digital learning may have been more salient for students in Germany (cf. Section 6.2). This could help explain why German students were more likely to report the use of digital learning media as a positive aspect. Rather than indicating that digital learning was implemented more effectively in Germany, this pattern may reflect differences in students' prior exposure to digital tools and, consequently, in how noticeable the pandemic-related shift toward digital media was. Students from households with higher cultural capital also evaluated digital tools more favorably, possibly reflecting a greater openness toward new media formats in these environments, as well as less frequent problems with unstable internet connections, resulting in fewer disruptions to learning [181].

In the present study, students who reported lower self-assessed learning success were also more likely to rate digital tools positively. This may indicate an appreciation of the accessibility or novelty of these tools, even if they did not necessarily translate into improved learning outcomes.

In contrast, a considerable number of students reported frequent technical difficulties as a negative aspect of distance learning. These challenges may be associated with several factors. First, the occurrence of technical problems likely reflects disparities in

students' access to digital resources at home, such as the availability of appropriate devices and the stability of internet connections. Students from households with more limited technological infrastructure may therefore have been disproportionately affected. Second, students' familiarity and proficiency in using digital devices and platforms may also have influenced the extent to which they experienced technical difficulties. From an instructional perspective, this suggests that, particularly under crisis conditions, teaching should rely on a limited set of well-established digital tools with which students are already familiar from regular classroom practice. In addition, the systematic integration of digital competencies into everyday instruction may help to build students' operational skills, thereby reducing the likelihood of technical problems during periods of distance learning and supporting a more effective use of digital media overall.

Beyond that, many students identified a lack of variety as a negative aspect of distance learning. This was reported more frequently by students who procrastinated less and rated their self-regulation more highly. These students may have higher expectations for engaging learning activities and may therefore be more sensitive to repetitive tasks [182]. A similar pattern was observed among students with fewer home learning resources, who may have experienced greater monotony due to limited access to recreational or stimulating activities. This finding aligns with research showing that students from lower SES backgrounds experienced reduced well-being during the pandemic [13,139].

When planning distance learning in future comparable situations, it might be meaningful for teachers to ensure that digital learning media are used thoughtfully and in a pedagogically meaningful way [183,184], as an excessive focus on digital tools may distract from learning content [185]. Interpreted within the integrative model of student well-being, differences in students' perceptions of digitally supported distance learning can be attributed primarily to the interplay between intrapersonal learning characteristics and contextual conditions, such as the resources and infrastructure of the home learning environment. This pattern suggests that the effectiveness and perception of digital learning are not determined by the availability of technology alone, but also by students' capacities to use these tools in a self-regulated manner. In addition, the digital progress achieved during the pandemic should be carefully maintained [54]. Future crisis teaching strategies might also ensure that students from disadvantaged backgrounds have access to varied and engaging learning experiences. Beyond that, teachers could design tasks that encourage students to leave their workstations and engage in more active learning activities [186]. Depending on the circumstances surrounding school closures, visits to extracurricular learning environments may also be considered [187].

6.6. Limitations

This study has several limitations that should be considered when interpreting the results. First, the structure of the questionnaire may have prompted students to reflect on both positive and negative aspects of distance learning, even if their overall perception was predominantly positive or negative. This potential suggestive effect implies that the frequency of positive and negative mentions cannot be directly compared.

Second, the sampling strategy limits the generalizability of the findings. Participation was based on an online survey, which may have attracted certain groups of students more than others. In addition, students without reliable internet access or appropriate digital devices—who were likely among those most affected by the challenges of distance learning—are underrepresented in the sample. Furthermore, the sample is unbalanced with respect to level of schooling, with primary school students being underrepresented. At the same time, the sample covers a wide age range. This heterogeneity should be considered when interpreting the findings, as developmental differences may influence both learning

behavior and the perception of distance learning (cf. Section 4.1). However, only weak associations between age and the other examined variables were observed (see Table A2), and age was included as a predictor in all random forest models. Because random forests estimate predictor effects conditionally on the values of other variables [188], age-related variation is taken into account when evaluating the importance of the other predictors.

Third, some constructs were measured using simplified indicators. Subjective learning success was assessed using a single mathematics-related item, which does not fully capture the complexity of students' learning experience. Similarly, although the examined SES indicators (e.g., number of books at home) are widely used in large-scale assessments (e.g., PISA) and have been shown to be robust and internationally comparable proxies for students' socioeconomic background, they remain only approximate measures of the underlying construct.

Fourth, the qualitatively informed quantitative research approach involved a data transformation in which qualitative responses were quantitized into binary variables indicating whether specific aspects were mentioned by students. While this approach enabled systematic quantitative analysis, it necessarily reduced the complexity and nuance of the original responses [189]. Further, the random forest analyses were restricted to the five most frequently mentioned positive and negative aspects of distance learning. This decision was made because these categories represented the most robust recurring themes in the dataset, showed sufficient prevalence for stable quantitative modeling, and enabled a parsimonious comparison across individuals. Less frequently mentioned categories remained part of the qualitative coding framework and were reported descriptively, but they were not included in the random forest models because their sparse occurrence would likely have reduced interpretability and model stability. At the same time, this focus represents a limitation, as potentially meaningful patterns associated with less frequently mentioned aspects may have remained undetected. Accordingly, the quantitative findings should be interpreted as referring to the most prevalent perceptions of distance learning rather than to the full range of students' reported experiences.

In addition, because the qualitative data were collected through open-ended questions, some responses were brief or fragmented and may therefore have been interpreted out of context, increasing the risk of misclassification. To mitigate this risk, the coding was conducted by two independent raters and finalized through a consensus coding procedure involving additional researchers.

Fifth, the identification of relevant predictors in the random forest models relied on a threshold for variable importance that was defined heuristically, as no universally accepted cut-off values exist [126,127]. This approach may have led to potentially relevant predictors being underemphasized if they did not exceed the selected threshold.

Sixth, the timing of the data collection—between April and July 2022—may have introduced recall bias, particularly in Switzerland, where containment measures had already been lifted for a longer period [190]. Moreover, because the analyses were conducted as a secondary analysis of data collected via an online questionnaire, it was not possible to collect follow-up data or clarify students' responses. As a result, some aspects may have been selectively reported, while others that also affected students' well-being may be underrepresented.

Finally, the cross-sectional nature of the data precludes causal interpretations. Although the analyses identify associations between predictors and students' perceptions of distance learning, causal conclusions cannot be drawn. In addition, the use of random forests entails methodological limitations, as this approach is often considered a "black box" [136,191] and is less intuitive to interpret than more traditional statistical methods such as regression models. Nevertheless, this method was deliberately chosen because it is particularly well suited to exploratory analyses and to datasets with uneven sample distributions [111]. To assess the robustness of the estimated random forest models, additional sensitivity analyses were performed.

6.7. Conclusions and Outreach

In summary, students' assessments of distance learning were highly diverse. Frequently reported positive aspects included the home environment, greater autonomy, and more free time, whereas common challenges comprised reduced social contact, insufficient learning support, and increased workload. Importantly, many of these aspects were perceived positively by some students and negatively by others. This ambivalence underscores the substantial heterogeneity in how students experienced and coped with the unprecedented situation and highlights the need to identify student-specific predictors in order to enable targeted educational support.

Against this backdrop, the present study contributes to the literature by conceptualizing students' perceptions of distance learning as experience-based indicators of their well-being during the COVID-19 pandemic [8,21–23]. Rather than relying solely on global or aggregated measures, this approach links well-being to concrete positively and negatively perceived learning experiences and thus provides a more fine-grained perspective on students' subjective appraisals of school closures. Empirically, the findings show that distance learning was not experienced uniformly but was associated with considerable variation in students' perceptions depending on learner-related, contextual, and broader background characteristics. By highlighting this heterogeneity, the study extends prior research that has often focused on average outcomes and offers more nuanced insights into students' experiences of distance learning. This underscores the importance of accounting for individual differences when designing educational interventions and policies, particularly in times of disruption.

Although the COVID-19 pandemic has receded, future comparable disruptions due to local or global waves of illness [28,192] or extreme weather events [29] remain likely. Notable recent examples leading to school closures include the 2024 floods in Spain [193] and the 2025 bushfires in Los Angeles [194]. It is therefore essential to apply the lessons from COVID-19 to future crises, placing students' perspectives at the center of planning, in order to prevent negative effects similar to those experienced during the COVID-19 pandemic. Specially developed guidelines can support this process by providing teachers and school administrators with recommendations on which aspects to consider when teaching under crisis conditions, thereby enabling productive distance learning while also addressing students' well-being [163].

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Abbreviations

The following abbreviations are used in this manuscript:

SES	Socioeconomic status
RQ	Research question
ROS	Random oversampling
ICE	Individual conditional expectation
CFI	Comparative Fit Index
RMSEA	Root Mean Square Error of Approximation
SRMR	Standardized Root Mean Square Residual
MSE	Mean Squared Error
ROC	Receiver operating characteristic
AUC	Area under ROC-curve
VI	Absolute variable importance
%VI	Percentage contribution to total variable importance

Appendix A

Table A1. Code tree for coding open-ended questions.

Like	**Dislike**
Fewer social contacts/less interaction *Fewer social contacts in general* *Less social pressure* *Protection against infection*	Type of teaching *Creating videos as an invasion of privacy* *No/too few conferences* *Grading* *Work assignments* *Higher workload*
Grading system *Better grades in general* *Less pressure* *Greater focus on creativity* *No class tests*	Support *General lack of support* *Insufficient treatment of teaching content* *No coordination between teachers* *Lack of feedback* *Difficulties in understanding* *Questions cannot be clarified* *Lack of consideration*
Learning format *Learning formats in general* *More intensive engagement with learning content/leading to better learning outcomes* *Lessons generally more relaxed/easier tasks* *Higher teacher commitment* *More individual support* *More creative/new types of tasks* *Independent/flexible work* *Use of digital/new learning media*	Burden *Lack of structure* *Distance between school and private life* *Family stress* *Fear of COVID*
Interesting new experience *Hidden curriculum* *Learning new things regardless of teaching content* *Learning how to be more independent*	Technical problems *Inhibitions about taking part in online lessons* *Teachers' low media literacy* *Problems/overloading of the internet platform used* *Failures of private internet connection*
Advantages of being at home *Being at home in general* *Fewer distractions/quieter learning environment* *More comfortable working environment* *Eating and drinking during lessons* *Wearing more comfortable clothes/not having to dress up* *Being able to sleep longer* *No need to commute to school* *Lessons start later*	Working environment *Procrastination* *Perceived learning success* *Lack of variety* *Lack of physical activity* *Being at home all the time* *Too much screen time* *Problems with independent work* *Motivation* *Frequent concentration difficulties/distraction*
More free time *More free time in general* *Spending more time with family* *Doing other things during lessons* *Lower workload*	Social contacts *Lack of social contacts in general* *Lack of class community*

Table A2. Descriptive statistics and correlation between the variables examined.

Variable	M	SD	Skewness	Kurtosis	1	2	3	4	5	6	7	8	9	10
1. Gender	0.32	0.47	0.76	−1.42		−0.081	0.131	−0.024	−0.136	−0.036	0.031	−0.063	0.054	−0.039
2. Age	15.95	2.19	−0.43	0.30	−0.081		−0.342	−0.081	−0.046	0.174	−0.134	0.248	−0.232	−0.156
3. Country of Schooling	0.19	0.39	1.62	0.62	0.131	−0.342		0.030	0.020	−0.146	0.090	−0.168	0.220	−0.066
4. First language	0.76	0.43	−1.19	−0.58	−0.024	−0.081	0.030		0.020	−0.010	0.051	−0.270	0.312	0.331
5. Self-regulation	2.87	0.51	−0.29	−0.13	−0.136	−0.046	0.020	0.020		−0.503	0.313	−0.085	0.023	0.092
6. Procrastination	2.95	0.81	0.15	−0.21	−0.036	0.174	−0.146	−0.010	−0.503		−0.391	0.083	−0.071	−0.051
7. Self-assessed learning success	2.91	1.17	−0.09	−0.75	0.031	−0.134	0.090	0.051	0.313	−0.391		−0.159	0.075	0.051
8. Equipped Workspace	1.16	0.18	1.19	1.27	−0.063	0.248	−0.168	−0.270	−0.085	0.083	−0.159		−0.435	−0.283
9. Equipped Household	2.76	0.63	−0.40	−0.53	0.054	−0.232	0.220	0.312	0.023	−0.071	0.075	−0.435		0.502
10. Number of books	3.98	2.04	0.05	−1.28	−0.039	−0.156	−0.066	0.331	0.092	−0.051	0.051	−0.283	0.502	

Note: Original coding of categorical variables*: Gender*: *Male* = 0, *Female* = 1; *Country of Schooling*: *Germany* = 0, *Switzerland* = 1; *First language*: *not German* = 0, *German* = 1; Columns with numbers represent Pearson correlation between the respective variables of the models and the dependent variables.

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