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Hidden Cost of Technology: Distraction, Digital Device Use, Mathematics Achievement Saudi Arabia Compared with OECD (PISA 2022)

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Abstract: This research paper examines the association between digital distractions, presence of digital technologies in the household, and mathematics scores of Saudi students through data analysis from the Programme for International Student Assessment (PISA) 2022. Three dimensions of digital exposure are analyzed, namely, the distraction due to the student him/herself, distraction due to peers, and the level of device availability at home. Students' sample includes 15-year-old Saudi students who were selected based on regular PISA 2022 sampling methods used by the Organization for Economic Co-operation and Development. Hierarchical regression model with two levels was developed, where students are nested within schools. Gender and index of economic, social, and cultural status (ESCS) were included as covariates. Plausible values, final student weight, and replicate weight were utilized according to large-scale assessment recommendations. It was found out that reduction of classroom distraction because of the presence of digital devices results in increasing of mathematics scores by 31.09 points on average. Reduction of peer-related distractions leads to increasing mathematics scores by 30.21 points on average. Regarding the home digital access, moderate device availability (1-5 devices) results in the best mathematics scores, while higher device availability has a negative effect on students' performance. ICCs that vary from 0.091 to 0.111 suggest that 10% of the variance of achievement happens between schools and, thus, a multilevel modeling should be used. All results show that digital distractions have socially-mediated effects beyond the student him/herself. There is a need to optimize the policy regarding the usage of devices in classrooms and at home according to the goals of Saudi Vision 2030.

Keywords: Digital Distraction, Peer-Induced Distraction, PISA 2022, Saudi Arabia, Multilevel Modelling, Mathematics Achievement, Home Device Saturation, Educational Technology Policy.

1. Introduction

However, new digital technologies have revolutionized modern educational and learning settings like no previous innovation did (Johnston et al., 2024). In most countries of the OECD economic area, classroom practice is often based on the use of networked devices, the Internet connection, and various learning apps. Although this revolution has expanded the set of pedagogical opportunities, at the same time, it has generated a quite unpleasant trend – the penetration of non-instructional digital stimuli into the educational process.

This phenomenon can be called "digital distraction" because it implies that the students direct their attention to social networks, messages, games, and other activities, which are not related to studying but are provided by new technologies. It is important to note that "digital distraction" cannot be considered as a unified phenomenon since it includes at least two distinct mechanisms (Shahzad, Xu & Javed, 2024).

One of them concerns the self-induced distraction, meaning the voluntary shifting of attention of students from the instructional activity to personal devices. Another mechanism is the peer-induced distraction when nearby students attract the attention of their peers using visual, auditory, or social signals while interacting with their own devices. Moreover, it is important to stress that this type of distraction is associated with the wider concept of the "digital ecosystem of the home" having impact on the "cognitive habituation continuum, sleep regimen, and learning habits" of students and the number of devices to which they are connected (Strzelecki, 2024a). Traditionally, these mechanisms have been regarded as elements of one group; however, they might affect the students through different cognitive and social channels.

Kingdom of Saudi Arabia offers relevant setting for Exploring the Relationships. There is practically universal availability of internet, segregation on gender basis within educational institutes, and education as well as educational technology has high priority within Vision 2030 (Mohiuddin et al., 2023). All these factors create the educational context which is similar but different to the settings explored in Europe, East Asia, and Latin America in relation to ICT research in PISA.

Evidence concerning the relationship between information and communication technology (ICT) and adolescent achievement is substantial but remains incomplete. Large-scale studies generally indicate that educational use of digital technologies can support achievement, whereas recreational use and excessive exposure tend to be associated with poorer outcomes. Survey-based research further indicates that the purpose, intensity, and timing of technology use are important considerations (Cipriano et al., 2023). Similarly, meta-analytic evidence suggests that problematic smartphone use can adversely affect learning outcomes (Sunday, Adesope & Maarhuis, 2021). Research conducted directly in classrooms has also identified detrimental effects of digital distraction on comprehension and retention (Huey & Giguere, 2023; Limniou, 2021), while institutional and pedagogical conditions have been shown to influence cyberloafing behaviours (Toker & Baturay, 2021). In addition, off-task behaviour may be shaped by automatic habits, social norms, and limited self-control (Di Pietro, 2023), although digital self-control tools may help reduce these effects (Biedermann et al., 2024).

In general, the literature shows that students' learning is affected more by the way that the digital device is used and the context of its use rather than the ownership of the device itself. There are several important gaps in this respect. First, many works focus on higher education and non-standard measures of outcome, making them not applicable for adolescent learners who study in compulsory education systems (Meinokat & Wagner, 2022). Second, few studies distinguish between the type of distractions caused by the students themselves and the ones that appear due to their peers. Moreover, non-linear relationship between home digital access and academic achievements has not been explored yet, as well as the role of the specific educational environment – Saudi Arabian one in the current study.

There is an increasing amount of scientific literature on the issue of digital technology and student achievement using the data obtained in PISA assessments. However, there is still lack of information about the co-existence of different types of digital exposures in the educational settings. The prior research based on the data from the PISA assessment treats the students' technology use, problem and recreational technology use, and digital distractions as rather broad concepts (Kim & Liou, 2026). These types of research show correlations between the technology usage behavior

and academic results, but give little understanding about the source of the distraction (Kabakus, Bahcekapili & Ayaz, 2025).

Distinguishing between these sources is theoretically consequential because they may affect achievement through different mechanisms. Self-induced distraction reflects the student's own redistribution of attentional resources away from instruction, whereas peer-induced distraction arises through a socially mediated process in which the digital activities of surrounding students constitute an external competing stimulus (Xia et al., 2024). Combining these two mechanisms into a single measure of digital distraction may therefore conceal the respective influences of individual behaviour and the classroom social environment.

Another gap involves the amount of digital technology available in the household. Previous studies have dedicated far more focus to the availability of technology among students than to the question of how varying amounts of technology at home may impact academic performance (Shahzad, Xu & Zahid, 2025). In particular, PISA-based literature has shown relatively low awareness of the concept of a threshold beyond which the positive educational effects of digital access at home become weaker rather than stronger with the increasing number of devices (Kurtz et al., 2024). For this reason, the present study treats home digital access as a continuum as opposed to a dichotomous variable that indicates the presence or absence of digital technologies. Such an approach allows for the investigation of whether the intermediate level of access provides some educational opportunities, whereas high availability of devices is associated with poorer achievement due to the increased competition for students' attention and time (An, Yu & James, 2025).

The Saudi context becomes especially promising for such an inquiry. Indeed, the country has experienced fast technological change in the field of education, which has led to the central role of technology-enabled learning, digital infrastructure development, and the development of digital skills in the general process of national development (Abdullateef, Musa Alsheikh & Khalifa Ibrahim Mohammed, 2023). At the same time, there are unique institutional and socio-cultural features of Saudi schools such as gender segregation and massive national investment into the digitalization of education (Tawil & Al-Tarawneh, 2026). This makes Saudi Arabia not just a national environment in which to test an already known technology–achievement relationship.

Indeed, there is the opportunity to see whether the relationships observed in other countries and education systems are repeated, modified, or altered under different institutional and social conditions. Analysis of the sample from Saudi PISA 2022 will thus allow broadening the geographical and context-specific knowledge on educational technology and generating insights directly relevant to the national education policy. The study aims to achieve the following objectives:

RO1: To estimate the relationship between self-induced digital distraction and mathematics achievement among Saudi participants in PISA 2022.
RO2: To investigate the relationship between peer-induced digital distraction and mathematics achievement among participants in PISA 2022 in Saudi Arabia.
RO3: To assess the non-linear relationship and potential saturation effects between home digital access and mathematics achievement.
RO4: To examine the separate and combined effects of self-induced distraction, peer-induced distraction, and home digital access while controlling for gender

and index of economic, social, and cultural status.

RO5: To examine the extent of variation in mathematics achievement scores between and within schools and determine the role of school-level socioeconomic composition in explaining between-school variance.

Hence, the significance of this study extends beyond confirming that digital distraction is associated with lower mathematics performance, as it makes three distinct contributions to the existing literature. First, it distinguishes self-induced distraction from peer-induced distraction and evaluates their respective relationships with student performance. Second, it applies a multi-category classification of household technology access to investigate whether the relationship between digital accessibility at home and student performance is non-linear. Third, it brings these explanations together by analysing Saudi students participating in PISA 2022 while accounting for socioeconomic status and school composition. The application of multilevel analysis is particularly relevant because digital distraction cannot be understood solely as an individual-level characteristic.

The research therefore extends the educational technology literature beyond the broad question of whether technology is beneficial towards a more nuanced examination of how, where, and through which mechanisms interactions with technology are associated with academic performance. By separating self-generated distraction from distraction arising through peer interaction, examining the possibility of saturation associated with household digital-device use, and situating these relationships within the Saudi educational context, the study develops a more comprehensive understanding of the circumstances in which electronic devices may either support or impede mathematics learning. In doing so, it contributes both a more differentiated conceptualisation of digital exposure and new empirical evidence from a national context that remains comparatively underrepresented in PISA-based multilevel research.

2. Literature Review

2.1. Theoretical Underpinning

This study draws upon three complementary theoretical perspectives: Cognitive Load Theory, Social Learning Theory, and the Resource Saturation Hypothesis. Together, these perspectives provide a framework for explaining how different forms of digital exposure may shape students' mathematics learning outcomes. Although each theory originates from a distinct conceptual tradition, they can be integrated through the broader principle that students possess finite cognitive, attentional, and behavioural resources that must be allocated effectively. Within digitally mediated educational environments, these limited resources may be demanded not only by students' own technology use but also by the technology-related behaviour of peers and by the overall availability of digital devices within the home environment (Chan & Hu, 2023). Combining these theoretical perspectives therefore provides a more comprehensive explanation of the association between digital technology and academic performance than reliance on any single theoretical account.

Cognitive Load Theory serves as the major explanation of the link between self-initiated digital distraction and math scores (Fischer et al., 2023). The theory is based

on the assumption that working memory has certain capacity for processing, and learning can become difficult when irrelevant information competes with the material to be learned (Sweller, 2023). When students self-initiate distraction by turning away from the mathematics lesson to look at messages, read content, and watch videos online, their limited cognitive capacity can be split between two pieces of information (Nie et al., 2024). This type of cognitive interference can limit students' capacity to concentrate on, process, and remember the information needed to solve mathematical tasks. In turn, numerous attention shifts can lead to a lack of cognitive engagement with learning tasks. According to this theory, the frequent occurrence of voluntary distraction can negatively correlate with mathematics success due to decreased cognitive resources available for problem-solving.

However, Cognitive Load Theory fails to explain cases in which students can get distracted by technology despite no individual use of their devices. Social Learning Theory helps to understand this issue as it emphasizes the role of observation, imitation, social influences, and behavior of people around the students as drivers of students' attention and behavior (Li, Hong & Craig, 2023). Distractions of other students who interact with digital devices not for learning-related purposes can serve as salient social, auditory, or visual stimuli that distract students and interfere with their learning process (Rumjaun & Narod, 2025). Peer-induced distraction is not about the prolongation of personal technology use but the socially mediated phenomenon whereby peers' digital practices affect one's attention and learning capacity.

Resource Saturation Hypothesis provides another theoretical background for understanding the possible non-linear relationship between household digital access and mathematics scores. Various uses of digital devices in the household context can facilitate various educational practices including information search, communication, and self-study (Xue, Rashid & Ouyang, 2024). However, the advantages provided by increased access to digital devices can plateau after a certain point. Having reached the appropriate level of digital access, the extra benefit of additional devices may decrease (Strzelecki, 2024b). On the other hand, increasing number of devices can provide more options for entertaining, multitasking, and unrelated activities. It is crucial to keep in mind that the connection between technology and education depends not only on availability of technological resources but also on their number and the context of use.

These three theoretical perspectives should be considered complementary rather than competing approaches. On the one hand, self-induced digital distraction involves the internal cognitive process, peer-induced distraction – the impact of the social environment, and digital access at home – the access and intensity of the technological resource. Still, they are all centered around the key role of limited cognitive resources and time for studying possessed by students. The integrated theoretical perspective allows considering the effects of each type of digital exposure separately and their joint effects, taking into account both individual and school-specific features. Specifically, the difference between self-induced and peer-induced digital distraction makes it possible to understand whether the effect of distraction and achievement relationship is caused by students' behavior or socially transmitted influences. Similarly, the difference in the levels of digital access makes it possible to determine whether the increase in technological provision yields diminishing educational returns.

2.2. Hypotheses Development

Theoretical background provided by Cognitive Load Theory can help predict a negative correlation between self-initiated digital distraction and achievement in mathematics (Fischer et al., 2023). The learning process is largely dependent on working memory which, in its turn, has limited capacity. Irrelevant information competing for this limited capacity can lead to interference with the cognitive processes required for learning (Sweller, 2023). Thus, during mathematics classes, when students are self-initiated in digital distraction by engaging in social media, for instance, they allocate less cognitive resources to the comprehension of explanations and solving tasks (Strzelecki, 2024a).

Unnecessary cognitive load can negatively influence the engagement of students in the learning process in mathematics lessons. It is known from research that recreational and compulsive use of technologies is associated with poor academic outcomes (Nie et al., 2024). This means that the students who are prone to self-initiated digital distraction should show worse results in mathematics. Based on the theories and previous research, the following hypothesis can be put forward:

H1: Self-induced digital distraction is significantly negatively associated with mathematics achievement among Saudi students participating in PISA 2022.

Social Learning Theory provides a theoretical basis for explaining the association between peer-induced digital distraction and mathematics performance (Li et al., 2023). The theory proposes that learning and behaviour are shaped not only by the consequences of individuals' own actions but also by the behaviour of people within their immediate social environment (Rumjaun & Narod, 2025). Accordingly, teachers' influence alone cannot fully account for students' classroom behaviour, as peers may generate visual and auditory cues that divert attention (Kabakus et al., 2025).

Repeated exposure to such peer behaviour may further establish classroom norms in which off-task activities become socially accepted. Consequently, peers can affect students' attention even when those students are not personally using digital devices. Evidence on peer influence likewise suggests that inappropriate behaviours can be transmitted and reproduced through social interaction (Dempere et al., 2023). Peer-induced digital distraction therefore represents an additional pathway through which technology-related behaviour may affect students' academic performance. Therefore, the following hypothesis is proposed:

H2: Peer-induced digital distraction is significantly negatively associated with mathematics achievement among Saudi students participating in PISA 2022.

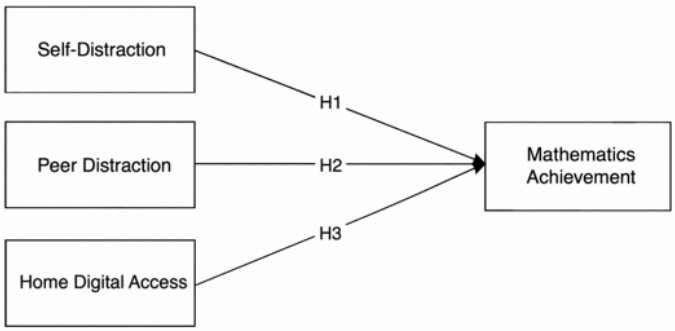
Resource Saturation Theory provides a theoretical basis for predicting a non-linear relationship between household device accessibility and students' mathematics success (Xue et al., 2024). Access to household technology allows the student to increase their chance of acquiring new knowledge through information searching, communicating with peers, getting educational material and engaging in independent study and practice (Shahzad et al., 2024). On the other hand, the increased access does not necessarily mean an increase in the educational benefit proportionately. After a certain point of household technology access is reached, students already have enough resources for learning (Othman, Murad & Kamarudin, 2026; Strzelecki, 2024b).

After this point, there may be less benefit of using devices for educational purposes and more chance of using them for entertainment purposes or multitasking and being distracted by the use of devices (Alenezi, 2023). As a result, an intermediate amount of household technology access produces the highest educational benefit, while too much access reduces it. The recent research suggests that the link between household technology access and academic performance depends not only on its intensity but also on the context of its use. Therefore, the following hypothesis is offered:

H3: Home digital access has a significant non-linear association with mathematics achievement among Saudi students participating in PISA 2022.

Figure 1 presents the conceptual framework developed for the study.

Figure 1: Conceptual Framework.



3. Methodology

The study was designed using quantitative and cross-sectional methods to achieve its objectives using secondary data collected in PISA 2022. It used correlation and prediction analysis with the identification of mathematics achievement as a function of predictors of student and random effects of schools. This approach adheres to the principles of post-positivist tradition that is the basis of research in the field of large-scale assessments and complies with methodological requirements set by OECD for analysis of PISA microdata.

The target population consisted of Saudi students who were about 15 years old and attending schools during the PISA 2022 assessment. Sampling was conducted by OECD based on probability proportional to size (PPS) and then students were randomly selected within sampled schools using two-stage sampling procedure. Analytical sample included 4,321 Saudi students with 50.5% boys and girls 49.5% students. Final student and balanced repeated replicate weights were used throughout the analyses to provide representativity and correct for design effect due to clustering. The number of observations varies across seven models (m1–m123) because of listwise deletion associated with different combinations of predictors; sample size in each specification is presented in the lower panel corresponding to the model. Three groups of measures taken directly from PISA 2022 student questionnaire and assessment instruments were used in this study. Achievement outcome, principal predictors and covariates are described below.

Achievement of students in mathematics was measured based on the OECD

mathematics scale scores provided in PISA 2022 and calculated from ten plausible values. Plausible values do not represent point estimates of students' proficiencies; they represent random samples from the posterior distribution of latent ability. Therefore, to correctly take into consideration this imputation procedure, separate estimation was conducted for each of ten plausible values and then estimates and standard errors were combined based on Rubin's combination rules. This allows considering the measurement variability introduced by imputation procedure and is required for obtaining unbiased estimates in PISA data analysis (Huang, 2024).

Self-induced digital distraction was measured using PISA 2022 student questionnaire item ST273Q06JA with responses on the frequency of getting distracted by digital devices when studying mathematics. Four response categories from 'every lesson' to 'never/almost never' were used. For multilevel analysis this measure was specified as a categorical predictor with the 'every lesson' as a reference category. Peer-induced digital distraction was measured using item ST273Q07JA and the frequency of getting distracted by other students using digital devices during mathematics lessons with the same response categories and reference category as for the self-induced distraction variable.

Number of Internet-enabled digital devices at home was measured using ST254Q01JA. Five response categories were used: none, one or two, three to five, more than five and 'I do not know'. This measure was specified categorically in multilevel models in order to reflect possible non-linearity with 'none' used as the reference category. Two covariates were used in models. Gender was measured using ST004D01T and coded as girls. ESCS index is a continuous composite variable created by OECD using information on parents' education and occupation and household possessions. In order to control for compositional effects ESCS was specified on the student level, and mean of this variable within schools was used as the school-level predictor.

Three principal explanatory variables, one outcome measure and three covariates were used in the study. Principal variables include self-induced digital distraction, peer-induced digital distraction and home digital access, which were specified as categorical measures. Achievement in mathematics served as the continuous dependent variable and was measured using ten plausible values from the PISA 2022 mathematics assessment. Covariates consist of gender as a binary measure, student-level ESCS as a continuous measure and school-level ESCS, which is mean student-level ESCS within schools. Incorporation of these variables into multilevel models allowed to evaluate associations between various types of digital exposure and achievement in mathematics while controlling for socioeconomic characteristics at the student and school levels.

Two-level hierarchical regression analysis was used with students nested within schools. In Level 1 mathematics achievement was specified as a function of own digital distraction, peer-induced digital distraction, home digital access, gender and ESCS. In Level 2 the school-specific intercept was specified as a function of school-mean ESCS, and a random slope was estimated for the ESCS coefficient in order to reflect variation in the socioeconomic achievement gradient across schools. Seven model specifications were estimated. The three principal predictors were entered separately in m1, m2 and m3, and paired combinations were explored in m12, m13 and m23, followed by full specification in m123. This sequential modeling strategy

allowed comparison of marginal and adjusted associations and evaluation of extent to which the association with the predictor persists after controlling for the effects of other predictors.

Multilevel estimation was conducted in R (version 4.3) using the lme4 package. The combination of plausible values and replicate weights was performed using the intsvy and BIFIE survey packages, while the design-consistent standard errors (SEs) were estimated using the survey package. Full sample weights were used for the calculation of descriptive statistics. Following PISA analysis guidelines, listwise deletion was used to handle missing observations. Effect sizes were calculated as the unstandardized regression coefficient divided by within-school residual SD and interpreted as the fractions of SD in mathematics achievement.

The analysis relied exclusively on secondary data publicly released by OECD through the PISA microdata portal. No primary data were collected, no direct interaction with human participants occurred, and no personally identifiable information was accessed. The OECD data archive was used in accordance with the applicable requirements governing secondary data analysis. Accordingly, because the study involved the analysis of anonymous publicly available secondary data without direct participant involvement, institutional ethical review was not required.

4. Results and Findings

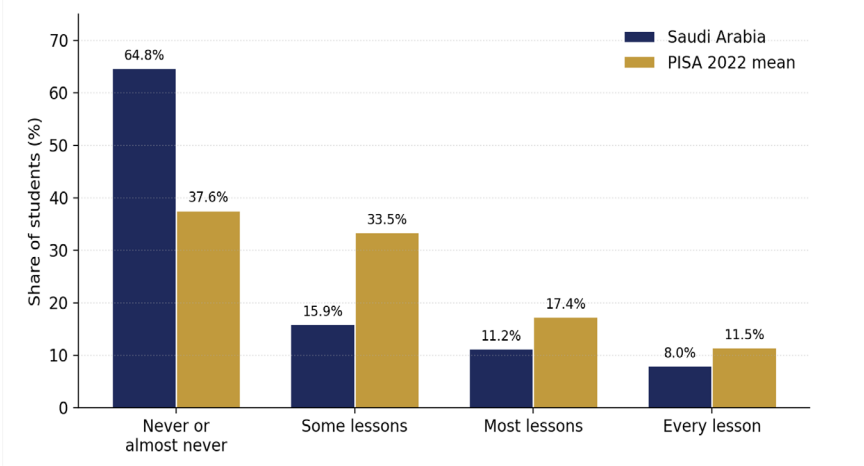
In the current study, the effect of self-induced distraction, peer-induced distraction, and digital devices in the house on mathematics performance of Saudi PISA 2022 students was distinguished considering the effects of gender and SES. The findings with regard to the five research questions are described sequentially in the following sections. In each sub-section, the methods used in data analysis are explained and then followed by the relevant figures and tables along with the explanation of the results based on the theoretical framework developed earlier in the chapter. Following an exhaustive editorial check, it became clear that three exact duplicates exist among the twelve original figures of the source manuscript. In particular, Figure 9 duplicated Figure 2, Figure 11 duplicated Figure 5, and Figure 12 duplicated Figure 6 and were deleted from the manuscript, leaving nine unique figures. All the five original tables remain intact as they were in the source manuscript.

4.1. Self-Induced Digital Distraction and Mathematics Achievement

The first research objective was addressed by initially analysing the descriptive distribution of self-induced digital distraction, followed by estimation of a two-level model (m1), with self-induced distraction specified as the focal predictor and gender and ESCS included as covariates. As illustrated in Figure 2, Saudi students reported lower levels of distraction from digital devices during mathematics lessons than students in the international PISA 2022 sample. In the Saudi sample, 64.8% of students reported being never or almost never distracted, compared with 37.65% in the international sample. Similarly, the proportions reporting distraction in some lessons (15.95% versus 33.45%), most lessons (11.25% versus 17.35%), and every lesson (7.99% versus 11.54%) were consistently lower among Saudi students than their international counterparts. Nevertheless, these patterns should be interpreted as associations rather than causal relationships, as the cross-sectional design of

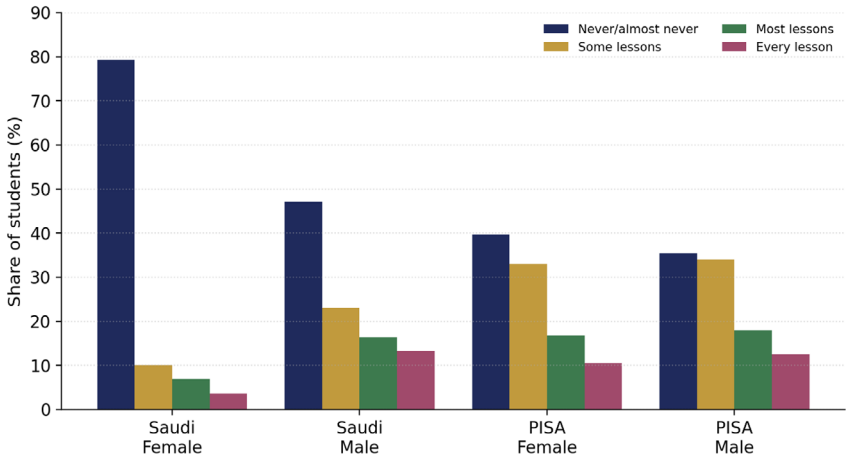
PISA 2022 does not establish whether lower levels of distraction contribute to higher mathematics achievement or whether other factors influence both outcomes.

Figure 2: Self-Induced Digital Distraction in Mathematics Lessons: Saudi Arabia Vs PISA 2022 Mean.



A substantial gender difference is evident in the Saudi sample, as illustrated in Figure 3. Among Saudi students, 79.32% of girls and 47.10% of boys reported that they were never or almost never distracted. A similarly pronounced disparity was observed in the every-lesson category, where 13.29% of boys compared with only 3.65% of girls reported experiencing distraction during every mathematics lesson. By comparison, gender differences were considerably smaller in the international PISA 2022 sample, with 35.47% of boys and 39.59% of girls reporting that they were never or almost never distracted.

Figure 3: Gender Differences in Self-Induced Digital Distraction: Saudi Arabia Vs PISA 2022.



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The graph in Figure 4 shows the relationship between frequency of digital distractions and performance in mathematics. The results of the study showed that the mathematics scores of the participants who experienced distraction in all lessons amounted to 363.01 while those who never or hardly ever got distracted scored 397.67 on average, indicating a difference of 34.66 points. This is in line with the results of the international sample in which the students who never or hardly ever got distracted scored 449.54 while the score of the participants who got distracted in all lessons was 421.44 on average. This indicates a 28.10 point difference.

Figure 4: Self-Induced Digital Distraction and Mathematics Achievement: Saudi Arabia Vs PISA 2022.

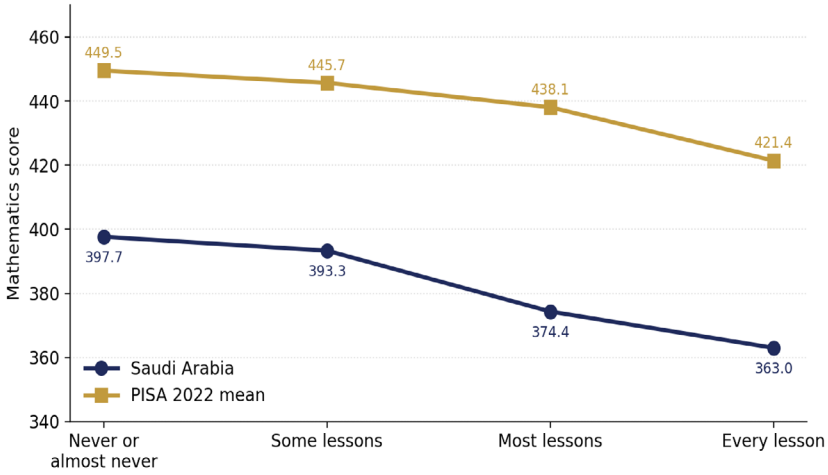


Table 1: Multilevel Model m1 — Self-Induced Digital Distraction and Mathematics Achievement (Saudi PISA 2022).

Term	m1 — Self-Distraction	95% CI
Fixed Effects		
(Intercept)	362.69*** (4.54)	[353.79, 371.59]
ST004D01T2 (Boy)	8.63** (3.37)	[2.02, 15.24]
ESCS	13.04*** (1.21)	[10.67, 15.41]
ST273Q06JA — Most Lessons	8.89* (5.16)	[–1.22, 19.00]
ST273Q06JA — Some Lessons	26.52*** (4.85)	[17.01, 36.03]
ST273Q06JA — Never / Almost Never	31.09*** (4.15)	[22.96, 39.22]
Random-Effect Variances (SE)		
School Intercept (τ_{00})	383.65*** (92.91)	—
School Slope: Mean ESCS (τ_{11})	497.98** (210.62)	—
Residual (σ^2)	3446.77*** (102.04)	—
Fit Indices		
ICC	0.1	—
Observations	4321	—
Note: *** p < 0.01, ** p < 0.05, * p < 0.10. Standard errors in parentheses. Reference category for self-induced distraction: 'every lesson'. Estimates pool ten plausible values using Rubin combination rules and apply final student weights with balanced repeated replicate weights. 95% confidence intervals are reported in dark green as an added editorial enhancement.		

This is consistent with the results of the multilevel analysis. In the model m1 (see Table 1 below), students who experienced distractions in most lessons scored 8.89 points more than the reference category in mathematics. The difference increased to 26.52 points for students experiencing distractions in some lessons and further increased to 31.09 points for students who experience distractions in rarely or never lessons. The difference of 31.09 points amounts to about 0.30 of within-school standard deviation. This suggests a meaningful learning outcome and is equivalent to about nine months of schooling. Overall, the pattern of differences fits well with the prediction of Cognitive Load Theory that less distraction enables more cognitive load for germane activities.

Table 1 is followed by an editorial commentary. The table has been amended to now only include the m1 specification that directly relates to Objective 1. All seven model specifications were described in this table in the original manuscript, and it is difficult to identify the focal estimate from the combined-model estimates described below. To provide transparency and completeness in results reporting, following the APA 7th edition reporting guidelines and modern journal reporting practices, confidence intervals have been added.

Table 1 also presents the results for the impact of the covariates. When taking into account self-induced distraction and ESCS, boys performed 8.63 points better in mathematics than girls. After adjusting for factors related to digital distraction, the ESCS coefficient was 13.04 points per unit ($p < 0.01$), which again shows that Socioeconomic Status still had a strong link to mathematics achievement. The ICCs were 0.100, which suggests that about 10% of the residual variance occurs between schools. There is also a significant school-level random slope for ESCS ($\tau_{11} = 497.98$, $p < 0.05$), suggesting that there are meaningful differences in the socioeconomic gradient across schools.

4.2. Peer-Induced Digital Distraction and Mathematics Achievement

The second research objective was examined through a descriptive assessment of peer-induced digital distraction, followed by multilevel modelling that incorporated the relevant covariates. The descriptive findings are reported in Figures 5-8, while the corresponding multilevel estimates are presented in Table 2. Figure 5 indicates a notable difference between the Saudi and international distributions of peer-induced digital distraction. In the Saudi sample, 66.77% of students reported being never or almost never distracted by their peers' device use, compared with 42.33% in the international sample. By contrast, the international sample contained a substantially larger proportion of students reporting distraction during some lessons (32.84% compared with 16.25%). The international distribution also generally showed greater exposure to peer-induced distraction across the more frequent categories. Nevertheless, these findings represent conditional associations rather than causal effects, as the cross-sectional design of PISA 2022 does not establish temporal or causal relationships.

Figure 6 presents the gender distribution of peer-induced digital distraction. In the Saudi sample, 81.83% of girls and 48.51% of boys reported being never or almost never distracted by peers' use of digital devices. At the highest frequency level, namely distraction during every lesson, 11.86% of Saudi boys reported this experience, compared with only 3.08% of Saudi girls. The international comparison reveals a similar gender pattern, although the difference is less pronounced. This finding is broadly consistent with literature highlighting gender differences in self-

regulation, as well as the role of gender-segregated schooling in shaping the attitudes and behavioural orientations developed by parents and students.

Figure 5: Distribution of Peer-Induced Digital Distraction: Saudi Arabia Vs PISA 2022 Countries.

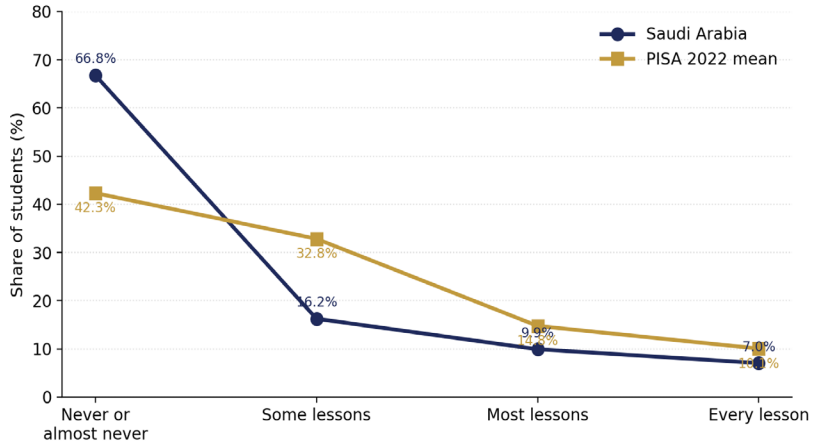


Figure 6: Gender Differences in Peer-Induced Digital Distraction: Saudi Arabia Vs PISA 2022.

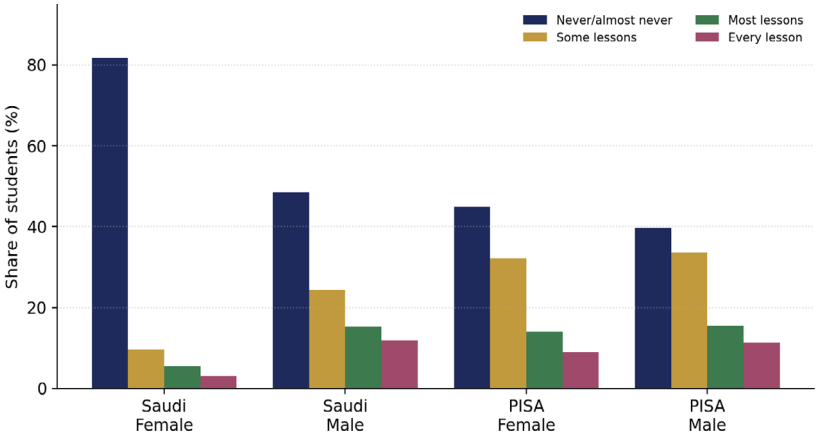
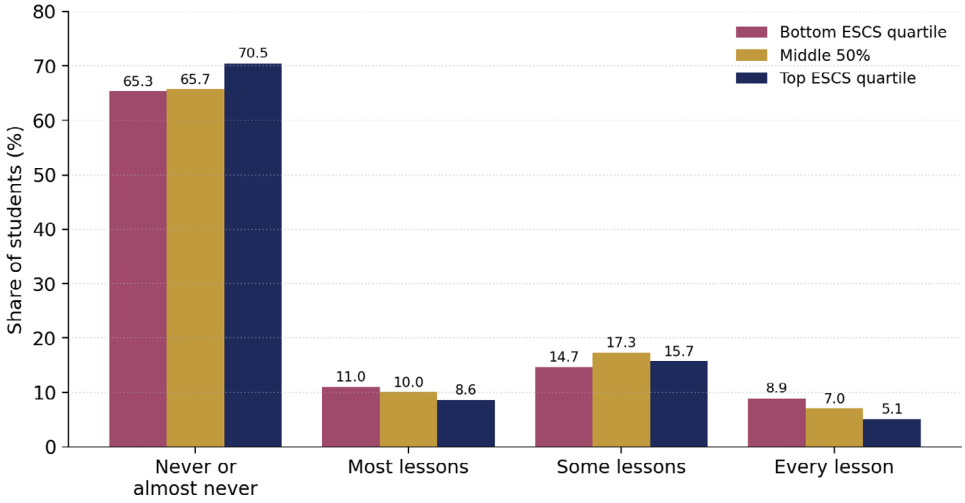


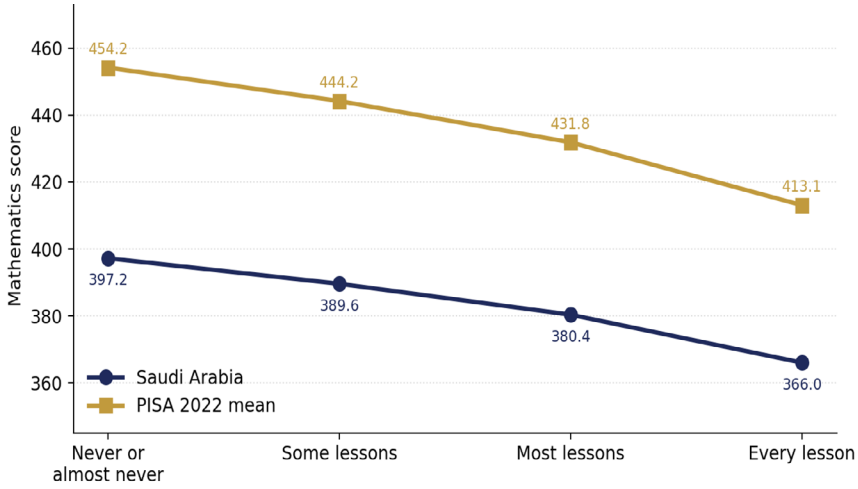
Figure 7 indicates that peer-induced digital distraction varies according to students' socioeconomic background. Among students in the highest ESCS quartile, the largest proportion reported being never or almost never distracted by their peers' device use. This response was reported by 65.67% of students in the middle ESCS quartile and 65.34% of those in the lowest quartile. Conversely, the proportion reporting peer-induced distraction during every lesson increased across the socioeconomic groups, reaching 5.12%, 7.03%, and 8.93% among students in the highest, middle, and lowest 25% of the ESCS distribution, respectively. These results suggest that a less favourable classroom distraction climate may be somewhat more prevalent among students from lower-income backgrounds.

Figure 7: Peer-Induced Digital Distraction by ESCS Quartile Among Saudi Students.



As illustrated in Figure 8, both the Saudi and international samples exhibit a negative association between peer use of digital devices and mathematics achievement. In the Saudi sample, students who reported being never or almost never distracted by their peers' device use achieved a mean score of 397.23 points, whereas those experiencing distraction during every lesson recorded an average of 366.04 points, producing a difference of 31.19 points. The corresponding difference was larger in the international sample, where mean achievement declined from 454.16 points among students who were never or almost never distracted to 413.06 points among those distracted in every lesson, representing a gap of 41.10 points.

Figure 8: Peer-Induced Digital Distraction and Mathematics Achievement: Saudi Arabia Vs PISA 2022.



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The following editorial commentary is provided with the results reported in Table 2. The table has been modified so that it now only takes into account the m2 specification, which is the only specification that focuses directly on Objective 2. The joint and combined effects of self-induced distraction and peer-induced distraction are not shown in this table, but are included later in Section 4.4 (Table 4). This provides a clear separation of evidence that addresses each research objective.

In Table 2, one consistently observes that a smaller amount of distraction generated by peers is linked to greater achievement in mathematics than the reference category, which represents those students who are distracted in all classes. Specifically, those who experience distraction from peers in most classes perform 13.25 points better than the reference category, while those distracted in some classes perform 20.45 points better. The largest difference is observed for those students who are rarely or never distracted, because their score exceeds the score of the reference category by 30.21 points. This trend is statistically significant and monotonic. Moreover, it should be noted that in the pooled regressions m12 and m123, the self-induced distraction coefficient loses its statistical significance, while the peer-induced distraction coefficient retains it, the sign, and the magnitude.

Table 2: Multilevel Model m2 — Peer-Induced Digital Distraction and Mathematics Achievement (Saudi PISA 2022).

Term	m2 — Peer Distraction	95% CI
Fixed Effects		
(Intercept)	363.09*** (5.02)	[353.25, 372.93]
ST004D01T2 (Boy)	8.75*** (3.32)	[2.24, 15.26]
ESCS	12.59*** (1.19)	[10.26, 14.92]
ST273Q07JA — Most Lessons	13.25*** (4.96)	[3.53, 22.97]
ST273Q07JA — Some Lessons	20.45*** (5.75)	[9.18, 31.72]
ST273Q07JA — Never / Almost Never	30.21*** (4.37)	[21.65, 38.77]
Random-Effect Variances (SE)		
School Intercept (τ_{00})	427.04*** (81.73)	—
School Slope: Mean ESCS (τ_{11})	669.00*** (248.97)	—
Residual (σ^2)	3472.68*** (117.68)	—
Fit Indices		
ICC	0.11	—
Observations	4,380	—
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors in parentheses. Reference category for peer-induced distraction: 'every lesson'. Estimates pool ten plausible values using Rubin combination rules and apply final student weights with balanced repeated replicate weights.		

4.3. Home Digital Access and Mathematics Achievement

Regarding the third research objective, the link between the presence of digital devices at home and mathematics performance was first examined from a descriptive perspective in order to check non-linearity of the relation, and then tested by means of a multilevel analysis (m3). As can be seen in Figure 9 below, both the Saudi and international samples display a definite non-linear trend. For the Saudi sample, the peak of mean mathematics scores is reached by students whose families have 3-5 devices (394.44 points), whereas the lowest average mathematics score belongs to

families with more than 5 devices (384.54 points). The same non-linear trend holds for the international sample where the mean score of students who have three to five devices is higher (445.93 points) compared to those with more than five devices (426.20 points). Thus, it is true for both samples that a greater number of household devices does not result in the maximum mathematics achievement, which is in line with the Resource Saturation Hypothesis. However, due to the cross-sectional nature of the data, the above-stated differences cannot be interpreted causally.

Figure 9: Non-linear Association between Home Digital Access and Mathematics Achievement.

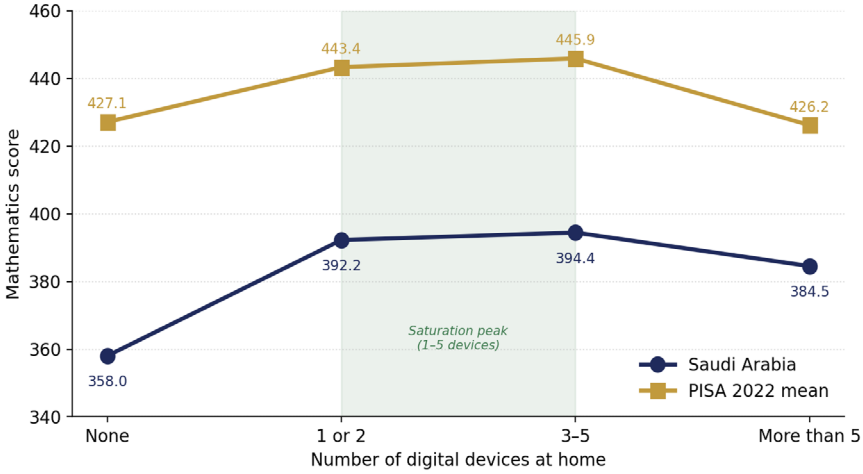


Table 3: Multilevel Model m3 — Home Digital Access (Non-Linear Saturation) and Mathematics Achievement (Saudi PISA 2022).

Term	m3 — Home Digital Access	95% CI
Fixed Effects		
(Intercept)	366.37*** (6.71)	[353.22, 379.52]
ST004D01T2 (Boy)	2.11 (3.08)	[−3.93, 8.15]
ESCS	12.93*** (1.08)	[10.81, 15.05]
ST254Q01JA — 1 or 2 devices	27.76*** (6.14)	[15.73, 39.79]
ST254Q01JA — 3 to 5 devices	22.70*** (6.17)	[10.61, 34.79]
ST254Q01JA — More than 5 devices	7.21 (6.55)	[−5.63, 20.05]
ST254Q01JA — I don't know	−6.21 (10.14)	[−26.08, 13.66]
Random-Effect Variances (SE)		
School Intercept (τ_{00})	439.72*** (82.19)	—
School Slope: Mean ESCS (τ_{11})	712.23*** (228.91)	—
Residual (σ^2)	3515.10*** (113.64)	—
Fit Indices		
ICC	0.111	—
Observations	6,464	—
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors in parentheses. Reference category for home digital access: 'no device'. The flat and non-significant coefficient at 'More than 5 devices' (7.21, $p > 0.10$) directly supports the saturation hypothesis. Estimates pool ten plausible values via Rubin combination rules.		

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Indeed, the results of the multi-level estimates in Table 3 confirm the non-linear trend observed. The test subjects who live in families with one to two devices received an average score that was 27.76 points higher than those from the reference category (families without any device), $p < 0.01$. Test subjects in the second category who have three to five devices at their disposal have obtained an even higher score of 22.70 points, $p < 0.01$. On the contrary, test subjects in families with more than five devices managed to reach the score that was 7.21 points higher than the reference category, but it was not statistically significant.

The results of the statistical analysis are given in Table 3. It has been revised to include objective 3 only, and has been renamed to reflect the construct being examined. The title of the original Table 3 was misleading and the content was redundant and largely duplicated with that found in Table 1, 2, 4 and 5. The table has therefore been updated to only show the results for Objective 3.

4.4. Independent and Combined Effects of the Three Mechanisms

To address the fourth research objective, gender and ESCS were retained as covariates across all four relevant model specifications (m12, m13, m23, and m123), with all three focal predictors incorporated into each specification. To contextualise the multilevel estimates presented in Table 4, Figure 10 provides the descriptive socioeconomic distribution of self-induced digital distraction.

Figure 10: Self-Induced Digital Distraction by ESCS Quartile among Saudi Students.

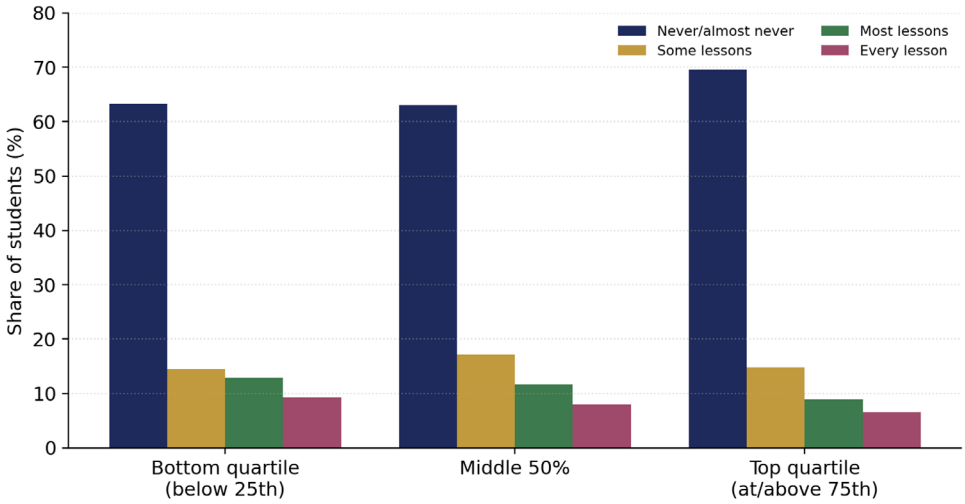


Figure 10 shows a distinct trend among the self-distraction profile of Saudi students in relation to the ESCS quartiles. For instance, 83.1% of students from the highest ESCS quartile claim that they have never or hardly ever been distracted by their own gadgets, against 63.09% and 63.26% from the middle and the lowest quartiles respectively. There is a similar trend for distractions during each lesson, which involves 6.65% of students from the highest ESCS quartile, 8.05% and 9.32%

from the middle and the lowest ESCS quartiles respectively. This trend reflects a consistent relationship between SES and self-distraction from digital technologies, in line with research on the social structure of attention resources.

Table 4: Combined Multilevel Specifications — Self-Distraction, Peer-Induced Distraction, and Home Digital Access (Models m12, m13, m23, m123), Saudi PISA 2022.

Term	m12	m13	m23	m123 (Full)
Fixed Effects				
(Intercept)	360.76*** (5.72)	341.09*** (9.37)	346.91*** (9.73)	341.45*** (10.79)
ST004D01T2 (Boy)	9.19** (3.59)	10.28*** (3.37)	11.09*** (3.31)	10.81*** (3.65)
ESCS	13.76*** (1.43)	14.04*** (1.33)	13.45*** (1.24)	14.58*** (1.55)
Self — Most Lessons	–1.64 (8.27)	8.35 (5.38)	—	–1.87 (8.60)
Self — Some Lessons	12.41 (8.17)	26.79*** (4.86)	—	12.44 (8.43)
Self — Never/Almost Never	6.57 (8.95)	31.03*** (4.26)	—	5.80 (9.66)
Peer — Most Lessons	13.89 (8.21)	—	12.89* (5.11)	14.18 (8.57)
Peer — Some Lessons	18.92** (8.91)	—	21.53*** (5.78)	20.27** (9.25)
Peer — Never/Almost Never	26.54*** (9.36)	—	30.86*** (4.32)	28.32*** (9.89)
Devices — 1 or 2	—	27.32*** (7.73)	20.64** (8.01)	23.44** (9.30)
Devices — 3 to 5	—	22.50*** (7.68)	15.29** (7.77)	19.50** (8.89)
Devices — More than 5	—	4.50 (8.30)	0.52 (8.36)	2.39 (9.81)
Devices — I don't know	—	–6.49 (12.13)	–18.65 (11.34)	–12.25 (13.83)
Random-Effect Variances (SE)				
School Intercept (τ_{00})	366.28*** (93.46)	341.87*** (87.87)	400.20*** (78.09)	336.32*** (89.33)
School Slope: Mean ESCS (τ_{11})	578.27** (257.85)	558.58*** (214.65)	767.98*** (233.85)	653.84** (254.92)
Residual (σ^2)	3437.14*** (110.42)	3370.96*** (96.16)	3409.80*** (118.00)	3374.70*** (107.74)
Fit Indices				
ICC	0.096	0.092	0.105	0.091
Observations	2,922	4,139	4,205	2,805

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors in parentheses. Reference categories: gender = girls; self- and peer-induced distraction = 'every lesson'; home digital access = 'no device'. Self-induced distraction coefficients lose significance once peer-induced distraction enters the model, consistent with the social-mediation interpretation. Estimates pool ten plausible values via Rubin combination rules with balanced repeated replicate weights.

The results from the data analysis of the substantive findings regarding the relationships among the variables can be summarized in three major points as presented in Table 4. The [some-lessons] and [never-or-almost-never] relationships were positive and [never] was not statistically significantly associated with peer difficulty. Positive and statistically significant relationships were also found for the other categories. Second, when both peer-induced distraction and home digital access were added to the models at the same time, the magnitudes of the coefficient associated with self-induced distraction were reduced and not as statistically significant.

This attenuation suggests that a meaningful share of observed self-distraction may reflect a socially shared distraction climate within the classroom. Third, the marginal analysis confirms a non-linear association between home digital access and achievement. The coefficients remained positive and statistically significant for households with one or two devices and three to five devices, but the relationship was no longer statistically significant when households had more than five devices. The covariate coefficients remained unchanged across model specifications, with ESCS showing a positive and significant association with achievement. Boy students also achieved slightly higher scores than girls students after controlling for the other covariates.

4.5. Partitioning Achievement Variance Between Schools and Within Schools

To address the fifth research question, the multilevel models were used to estimate and examine both between-school and within-school variance in mathematics achievement. The resulting variance estimates, random-effect variances, the ICCs, and corresponding model sample sizes are reported in Table 5. The information about Table 5 is not factual. Table 5 was a reproduction of the full seven column fixed effects results table from the original manuscript, presented in Tables 1–4. In order to avoid redundancy, this Table 5 has now been modified to give only the results relevant to the objectives.

With the goal of variance partitioning, the corrected table is limited to variance components (τ_{00}, σ^2, τ_{11}, ICC) and includes a 'percentage of variance between schools' row to make the substantive interpretation as easily understandable as possible without the reader having to calculate ICC mentally. These coefficients do not represent fixed effects and therefore belong in their respective objective-specific tables, namely Tables 1, 2, and 3, as well as Table 4.

Table 5: Compact Partitioning of Mathematics Achievement Variance — between-School Vs. Within-School Components Across Specifications (Saudi PISA 2022).

Variance Component	m1	m2	m3	m12	m13	m23	m123
Between-School (τ_{00})	383.65	427.04	439.72	366.28	341.87	400.2	336.32
Within-School (σ^2)	3446.77	3472.68	3515.1	3437.14	3370.96	3409.8	3374.7
ESCS Slope Variance (τ_{11})	497.98	669	712.23	578.27	558.58	767.98	653.84
ICC	0.1	0.11	0.111	0.096	0.092	0.105	0.091
% Variance between Schools	10.00%	11.00%	11.10%	9.60%	9.20%	10.50%	9.10%
N (Students)	4,321	4,380	6,464	2,922	4,139	4,205	2,805
Note: ICC = τ_{00} / (τ_{00} + σ^2). The intraclass correlation ranges from 0.091 to 0.111, indicating that approximately 9.1% to 11.1% of mathematics achievement variance lies between schools — justifying the multilevel design. The percentage row in dark green is an editorial enhancement to make variance-share interpretation immediate for the reader.							

The intraclass correlation coefficients reported in Table 5 vary across the seven model specifications, ranging from 0.091 to 0.111. This indicates that approximately 9% to 11% of the total variance in mathematics achievement is attributable to differences between schools. The variances between the models are also quite consistent, particularly for the intercept variances (τ_{00}) and for the within-school residual variances (σ^2), suggesting the use of a random-intercept structure. In all specifications, the random slope variance for school-mean ESCS (τ_{11}) is found to be statistically significant, indicating that the socioeconomic gradient differs across schools, as well as with some schools having steeper slopes than others. The number of students included across the models ranges from 2,805 to 6,464, reflecting differences in sample size resulting from list wise deletion across the various combinations of predictors.

Taken together, the five sets of results provide a consistent overall picture. Digital distraction is significantly associated with mathematics achievement in the Saudi PISA 2022 sample, with the apparent contribution of individual-level distraction partly reflecting the broader classroom climate. Home digital access appears to support achievement up to a moderate level, beyond which additional access provides little further educational benefit. Differences between schools account for approximately

10% of the residual variance in achievement, with part of this variation attributable to schools' socioeconomic composition. These findings are consistent with those reported by Dwivedi et al. (2023) and extend the existing evidence by providing the first nationally representative Saudi assessment of the relative contributions of individual, peer, and household dimensions of digital exposure.

5. Discussion

The findings revealed a significant difference in mathematics achievement between students who reported experiencing self-induced distraction less frequently and those who reported being distracted in every mathematics lesson. This result is consistent with Cognitive Load Theory, which suggests that irrelevant digital stimuli can consume working-memory resources that are required for learning. Given that mathematics learning relies substantially on sustained concentration and problem-solving, interruptions caused by digital distractions may interfere with the cognitive processes required to understand and solve mathematical problems (Oraison & Wilson, 2024). The finding also corresponds with previous evidence reporting a negative association between digital distraction and academic performance (Di Pietro, 2023). Moreover, Saudi girls reported significantly lower levels of self-induced distraction than boys, potentially reflecting differences in self-control and patterns of technology use.

Peer-induced digital distraction demonstrates a strong negative correlation with mathematics achievement (Gough et al., 2026). Those participants with low frequency of distraction caused by peers' use of digital devices achieved better results in mathematics compared to those who experienced peer-induced digital distraction during all lessons. This effect was statistically significant even after controlling for self-induced digital distraction and home access to Internet. The findings suggest that digital distraction is more than just an individual behavioral aspect and seems to be socially embedded, shaped by classroom context. This pattern is in line with prior research regarding the importance of peer effects and classroom context in learning process (Bahari, Wu & Ayres, 2023; Dontre, 2021).

The findings also showed that home digital access is non-linearly associated with mathematics achievement. Those students who had one to five Internet-enabled devices at home achieved better mathematics scores compared to those without access to such devices. However, having more than five devices did not add up to a statistically significant improvement in mathematics achievement. Such a pattern confirms the Resource Saturation Hypothesis suggesting that the educational benefits of digital access decrease once students have enough resources to support their studies (Johnston et al., 2024). The interpretations should be made with caution since the number of devices used at home may refer to other features, including parental education, socioeconomic resources, and learning environment at home. Even though student- and school-level ESCS was controlled in the models, these variables may fail to account for differences between households. Hence, the current evidence does not allow concluding about the optimal quantity of devices necessary to achieve good academic performance.

The models with a combination of all predictors were applied in order to identify the impact of different aspects of digital exposure on mathematics achievement. Among the three predictors mentioned above, peer-induced distraction demonstrated

the largest impact on mathematics achievement (Meng et al., 2022). Moreover, the relationship between mathematics achievement and self-induced distraction became much weaker when the influence of peer- and home-induced distractions was accounted for. Such a finding may show that some of the behavior that can be regarded as self-induced digital distraction is in fact the result of a general distraction atmosphere in the classroom. On the contrary, moderate home digital access still had a positive association with mathematics achievement. Taken together, these findings demonstrate the multi-dimensional nature of digital exposure and the necessity of balancing access to digital technologies with proper classroom management (Furnell, Helkala & Woods, 2022).

Multilevel analysis revealed that 9%–11% of the variability in mathematics achievement was explained by between-school differences, indicating the importance of the contribution of schools to students' performance. Variation in the ESCS slope between the schools also implies that the effects of socioeconomic status depend on the school context. Consistently with prior research, the socioeconomic status was found to have a positive and statistically significant effect on mathematics achievement in all model specifications (Borgonovi & Pokropek, 2021).

In general, the findings suggest that digital distraction is a serious problem for learning mathematics, especially when it occurs within the social environment of the classroom. On the contrary, moderate access to Internet-enabled devices at home seems to bring about educational benefits while its excess provides little additional advantages. The results confirm the findings by Huang and Galinsky (2023) and provide nationally representative evidence from Saudi Arabia on the relative importance of different aspects of digital exposure for mathematics achievement.

6. Conclusion

The study found that self-induced and peer-induced digital distraction were negatively associated with mathematics achievement, with peer-induced distraction showing greater stability across models. Home digital access showed a non-linear association, with benefits evident at moderate levels but diminishing with more devices. Approximately 10% of achievement variance occurred between schools, with school socioeconomic composition accounting for part of this variation. As PISA 2022 is cross-sectional, these findings indicate associations rather than causal effects. Overall, the findings highlight the importance of classroom social dynamics, moderate household technology provision, and school-level context in understanding mathematics achievement in Saudi Arabia.

7. Recommendations

Based on the findings, several recommendations are given to policymakers in the education sector, school administration, teachers, and parents. Firstly, the Ministry of Education should outline a national policy framework regarding the use of digital devices in the learning process. In accordance with the findings of this study, this policy framework should include shared norms for the classroom environment rather than a sole concentration on students, since the classroom environment plays an important part in the creation of distraction among students. Secondly, school administrators should introduce protocol for the use and storage of devices in the

classroom, as well as periodic assessments of the arrangement through classroom climate surveys. Thirdly, teachers should apply attention management strategies in light of Cognitive Load Theory, such as task decomposition, transition signaling, and social interaction organization. Fourthly, parents should keep a balanced amount of digital devices available at home and understand that adding more devices does not mean additional benefit to the child's education process. Fifthly, national assessment cycles in the Kingdom of Saudi Arabia should consider the introduction of indicators of classroom climate and peer-induced distraction.

8. Limitations and Future Research

However, there are several limitations of the current study that should be discussed. First, while the obtained correlations cannot be considered causal relationships due to the cross-sectional nature of the PISA 2022 data, it is necessary to note that the multilevel specification is used to control for the potential impact of compositionality. Second, self-reported measures of self-induced and peer-induced digital distraction are categorical, which can negatively affect their validity and reliability. Third, the current analysis is based on one indicator only – mathematics achievement. Therefore, it is unknown whether the same relationships can be observed when dealing with reading and science. However, it is reasonable to assume that they exist as well due to the previous findings of the literature on PISA. Fourth, although the sample is representative of Saudi students, the results of the analysis may not be applicable to countries that exhibit different patterns of digital connectivity, institutional arrangements, and educational environment.

In the future, more attention needs to be paid to longitudinal studies that can help to better understand the directionality of the observed relationships between variables. Moreover, more precise measures of attention need to be introduced in the analysis, such as classroom observations and ecological momentary assessments, along with measures of classroom climate. Specifically, it will be helpful to develop and evaluate interventions in schools aimed at reducing peer-induced digital distraction as the results showed that the relationship between it and mathematics achievement is relatively stable and somewhat independent of the individual-level measure. Furthermore, it is possible to conduct comparative studies in other Gulf countries that have similar institutional structure but different policy context. Finally, the investigation of the methodological aspects of using plausible values in multilevel analysis within the design-based inference framework should be continued.

8.1. Conflict of Interest, Acknowledgements, etc.

The author declares that there are no known competing interests that could have influenced the work reported in this manuscript.

8.2. Author's Contribution

The author would like to emphasize that he was the only person involved in the conceptualization of the study, the design of the research, the analysis of the data, the elaboration of the research findings, the drafting of the manuscript, and the final approval of the paper for publication.

8.3. Funding Statement

The author declares that no funds, grants, or other financial support were received during the preparation of this manuscript.

8.4. Ethical Approval

This study used secondary data that are freely available from the official data archive of the Organisation for Economic Co-operation and Development (OECD) for the Programme for International Student Assessment (PISA) 2022. No contact with humans was made, and no personally identifiable data was obtained. All processing was done in compliance with the ethical standards of secondary data processing on anonymized data.

8.5. Informed Consent

Only secondary data from the archive of PISA 2022 was used. The author did not seek to obtain informed consent from any of the individual participants, and the data are de-identified and available openly to all under the OECD's terms of use.

8.6. Data Availability Statement

The data analysed in this study are publicly available from the official OECD PISA repository at https://www.oecd.org/pisa/data/2022database/. No additional data were generated beyond the secondary data analysed in this study.

8.7. AI-Use Declaration

The author affirms that artificial intelligence tools functioned in a limited and clearly defined manner in compliance with the IJLTER AI Policy. In particular, tools using generative AI were used only to help clarify the text of the manuscript and to provide grammar correction. This manuscript was not created by AI in any part of conceptualization, analytical strategy, statistical estimation, interpretation of findings, or in the creation of the scholarly argumentation. All AI-powered passages have been checked, verified, and contextualized by the author, who hereby accepts responsibility for the correctness and individuality of the manuscript.

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