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Impacto de las tecnologías emergentes en el desarrollo cognitivo: el papel mediador del apoyo social digital entre estudiantes de educación superior

Impact of emerging technologies on cognitive development: the mediating role of digital social support among higher education students

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RESUMEN

El objetivo del presente estudio es explorar las relaciones directas e indirectas entre la tecnología emergente y el desarrollo cognitivo. Este estudio utilizó un diseño de investigación transversal, empleando un enfoque de encuesta por cuestionario para la recopilación de datos de estudiantes de educación superior. Se utilizó la escala Likert de múltiples puntos para medir la tecnología emergente, el desarrollo cognitivo y el apoyo social digital. Se recopilaron datos de 500 estudiantes, tanto hombres como mujeres, que estudiaban en universidades chinas. Se aplicó el enfoque PLS-SEM para analizar la relación estructural entre las variables dadas en este estudio de investigación. Los hallazgos del estudio indicaron que la tecnología emergente tiene una relación positiva y significativa con el desarrollo cognitivo, y que el apoyo social digital media positiva y significativamente la conexión entre la tecnología emergente y el desarrollo cognitivo entre los estudiantes de educación superior. Se concluyó que tanto la tecnología emergente como el apoyo social digital son predictores del desarrollo cognitivo de los estudiantes en el nivel de educación

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superior. El estudio contribuye a la literatura sobre tecnología emergente, desarrollo cognitivo y apoyo social digital en el contexto de la educación superior. Este estudio proporciona valiosas implicaciones teóricas y prácticas para profesores, psicólogos y desarrolladores de planes de estudio en el nivel de educación superior.

PALABRAS CLAVE

Tecnología Emergente; Desarrollo Cognitivo; Apoyo Social Digital; Estudiantes de Educación Superior.

ABSTRACT

The aim of the current study is to explore the direct and indirect relationships between emerging technology and cognitive development. This study utilized a cross-sectional research design, employing a questionnaire survey approach for data collection from students in higher education. The multi-point Likert scale was used to measure emerging technology, cognitive development, and digital social support. Data were collected from 500 students, both male and female, studying at Chinese universities. The PLS-SEM approach was applied to analyze the structural relationship among the given variables in this research study. Findings of the study indicated that emerging technology has a positive and significant relationship with cognitive development, and that digital social support positively and significantly mediates the connection between emerging technology and cognitive development among higher education students. It was concluded that both emerging technology and digital social support are predictors of students' cognitive development at the higher education level. The study contributes to the literature on emerging technology, cognitive development, and digital social support in the context of higher education. This study provides valuable theoretical and practical implications for teachers, psychologists, and curriculum developers at the higher education level.

KEYWORDS

Emerging Technology; Cognitive Development; Digital Social Support; Higher Education Students.

1. INTRODUCTION.

The world become a global village just because of digital technology, which includes the internet, digital devices, smart devices, virtual or augmented reality, and other technologies. During the COVID-19 pandemic, emerging technology has become more vital to the workforce. In this context, several studies conducted to examine the impact of emerging technology on the cognitive development of humans. Over time it remains a central topic and has appeared to learn more about the impact of digital technology on the cognitive development of youth. As students navigate through this critical phase of their lives, they encounter numerous academic, social, and personal changes that can shape their cognitive abilities and overall well-being (Dunn et al., 2008) Concurrently, digital social support has emerged as a prominent feature in the lives of higher education students, providing them with a platform to connect, seek guidance, and engage with their peers and mentors (Peters & Romero, 2019). The convergence of these two phenomena emerging technologies and digital social support has sparked interest in understanding how they interact and influence cognitive development among students (Bygstad et al., 2022). This article aims to explore the mediating role of digital social support in the relationship between emerging technologies and cognitive development among higher education students, shedding light on the intricate dynamics at play in this evolving landscape.

New and advanced technologies like virtual reality, augmented reality, artificial intelligence, and machine learning are changing how we use and interact with technology. These technologies can help us learn and develop our thinking abilities in exciting ways (Getuli et al., 2020). They offer interactive and immersive experiences that can improve our attention, memory, and problem-solving skills. In other words, they make learning more fun and effective (Ilić et al., 2021). Furthermore, these emerging technologies have been discovered to enhance student engagement and motivation, resulting in improved academic performance (Zhu et al., 2022).

However, it is important to note that some studies have also indicated potential negative effects of emerging technologies on cognitive development, specifically concerning attention and memory (Small et al., 2022). Excessive use of smartphones and engagement with social media platforms have been associated with reduced attention span and decreased performance in memory tasks (Lepp et al., 2015). Consequently, conducting research to examine the influence of emerging technologies on cognitive development becomes crucial in order to establish guidelines for their optimal utilization in higher education.

Digital social support refers to the wide range of technological platforms and applications that offer virtual communities, support networks, and resources to individuals. One notable component of digital social support is Virtual Reality (VR), which provides immersive experiences by using computer-generated environments(Small et al., 2022). With VR, users can interact with others, explore various settings, and participate in collaborative activities, fostering a sense of presence and connection (Pellas et al., 2020).

Studies show that social support facilitated by Virtual Reality (VR) can enhance emotional health, lessen feelings of loneliness, and promote social bonds, especially for those who experience physical or geographic barriers to traditional support systems (Torous et al., 2021). Furthermore, VR platforms present opportunities for participation in support groups, counseling meetings, and therapeutic initiatives, fostering an atmosphere of inclusivity and comprehension. The immersive encounters enabled by VR foster substantial relationships and allow people to experience the advantages of support and therapy in a novel and significant manner (Antoniou et al., 2017).

Augmented Reality (AR), a crucial component of digital social support, integrates digital data into the real world, thus merging virtual and tangible realities effortlessly (Marques et al., 2022). By facilitating real-time sharing of information, collaboration, and engagement, AR amplifies social interactions. For instance, AR platforms enable distant communication by allowing users to interact visually even in the face of physical separation. Furthermore, AR grants immediate availability of relevant data, resources, and professional advice, hence providing practical assistance and direction (Javornik et al., 2022). Recent research underscores the impact of AR in promoting social bonds, honing communication competencies, and boosting problem-solving skills, particularly within academic and work settings (Bistaman et al., 2018). Utilizing AR technology, digital social support can reconcile the divide between physical and virtual communications, fostering significant relationships and equipping individuals.

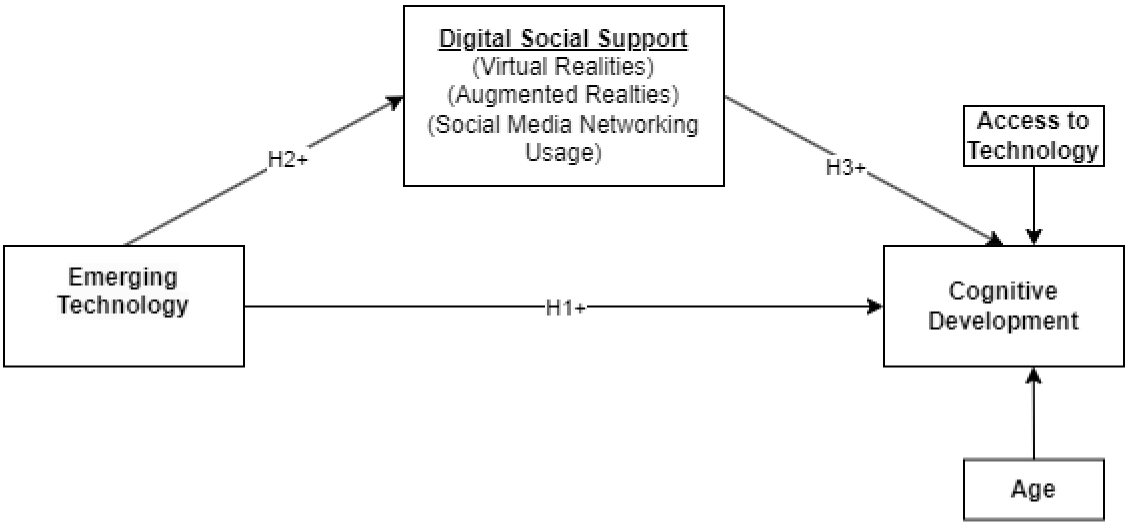
Another significant facet of digital social support is the utilization of social media networks, which enable individuals to establish connections, converse, and garner aid from others across various internet platforms. Widely-used networks like Facebook, Twitter, and Instagram serve as platforms where people can express their feelings, share experiences, and discuss challenges, thereby fostering a sense of community and acceptance (Ochonogor & Mutula, 2020). These platforms further facilitate the formation of virtual support groups, where individuals with shared interests or experiences can congregate to provide emotional backing, share knowledge, and offer practical tips. Studies indicate that social media usage can positively affect mental health and overall well-being, emphasizing its potential to alleviate feelings of isolation, augment social support, and encourage self-expression. (Popat & Tarrant, 2023). It is a vital factor in determining academic success, as higher levels of cognitive development have been linked to better academic performance and increased opportunities in one's career. (López-González, 2023). Several studies have reported the positive effects of cognitive training on cognitive development, particularly in older adults (Klimova, 2016).

In the context of Chinese higher education, a significant research gap exists concerning the impact of emerging technologies on cognitive development and the role of digital social support. Emerging technologies are increasingly prevalent in educational settings, yet specific research in China remains scant. The effects of these technologies on the cognitive development of Chinese students are not thoroughly understood, and the functionality of digital social support in Chinese higher education is similarly underexplored. Therefore, additional research is warranted to investigate these domains and to address this knowledge deficit within Chinese higher education. Therefore, this study is to investigate the impact of emerging technologies on cognitive development among higher education students and the mediating role of digital support. Specifically, we aim to test three hypotheses:

> H1: Emerging technologies have a significant and positive impact on cognitive development among higher education students.
>
> H2: Digital social support has a significant and positive impact on cognitive development among higher education students.
>
> H3: Digital support mediates the relationship between emerging technologies and cognitive development among higher education students.

By conducting this study, our aim is to gain a deeper understanding of the intricate relationship between technology, digital support, and cognitive development within the realm of higher education.

Figure 1. Conceptual framework that hypothesizes a relationship between emerging technology, mental health, digital social support.



2. MATERIALS AND METHODS.

Study Design and Participants.

This research employed a cross-sectional survey approach. In a cross-sectional study, the investigator measures the outcome and the exposures in the study participants at the same time (Hennekens & Buring, 1987). The study's subjects were tertiary education students hailing from diverse universities across China. Selection of these participants was facilitated through a convenience sampling technique. Eligibility for the study was determined by two criteria: current enrollment in a higher education institution and access to contemporary technologies like smartphones and laptops. Those who did not meet these specifications were not considered for the study.

The study managed to enlist 500 participants, evenly split with 250 males and 250 females. The participants, aged between 18 and 30 years, originated from a diverse array of academic disciplines. The study employed a self-directed survey divided into four sections: personal demographics, use of current technologies, digital social support, and cognitive development. To cater to all participants, the survey was made available in both English and Chinese. It was disseminated through a digital platform for easy accessibility and convenience. Participation was wholly voluntary with all participants being briefed about the study's goals and assured of the confidentiality and anonymity of their responses.

Instrument Development.

In this study, emerging technology was examined as the independent variable, cognitive development as a dependent variable and, digital social support attended as the mediator variable. For the collection of required data, a questionnaire was designed consisting two parts. The first one part consists demographic information such as; gender, year of study, and major of the respondents. Additionally, this section included instructions, as well as statements ensuring anonymity and privacy. While in second part, respondents were required to rate the given item related with Emerging technology, cognitive development, and digital social support. There were eight items for each construct. The multi-point Likert scale were used. The reliability of the scale was measured by using a threshold value of 0.07. Additionally, Table 2 provides information on the convergent and discriminant validity of the variables.

Measures.

Emerging Technology.

In this study eight statements related to emerging technology were adapted from the work of (Sosa et al., 2022). It was seven-point Liker type scale having response range from one to seven "Almost Never to Almost Always". Where Sample statements were used "virtual reality, augmented reality, artificial intelligence, and mobile applications.". The emerging technology scale adapted for this research was valid and have acceptable internal consistency, where the Cronbach's Alpha value was 0.657.

Cognitive Development.

In this study three statements related to cognitive development were adapted from the work of (Shokoohi-Yekta et al., 2013). It was five-point Liker type scale having response range from one to five "1 (strongly disagree) to 5 (strongly agree). Where Sample statements were used such as " attention span, memory, and problem-solving abilities.". The cognitive development scale adapted for this research was valid and have acceptable internal consistency, where the Cronbach's Alpha value was 0.657.

Digital Social Support.

The final scale was used the digital social support scale, statements related to digital social support were adapted from the work of (Sharma & Devkota, 2019) It was five-point Liker type scale having response range from one to five "1 (strongly disagree) to 5 (strongly agree)". Such as "social media platforms, emails, and instant messaging.". The digital social support scale adapted for this study was valid and have acceptable internal consistency, where the Cronbach's Alpha value was 0.801.

Data Collection.

The process of data collection in research pertains to the organized accumulation of pertinent data needed to study a particular issue or phenomenon. This involves gathering raw numbers, observations, or measures that form the basis for analysis and conclusion in a research study (Pandey & Pandey, 2021). The primary method of data collection for this investigation was

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through the use of surveys. These surveys were designed to glean information on the focal points of the study, namely the usage of cutting-edge technologies, digital social assistance, and cognitive growth among higher education students across various Chinese universities.

Data gathering occurred in two distinct phases. During the initial phase, participants were requested to fill out a preliminary survey. This survey captured demographic details such as age, gender, and the academic course the student was enrolled in. Additionally, it gathered data concerning the main focus areas of the study: usage of advanced technologies, digital social support, and cognitive development.

Data Analysis.

In this particular investigation, we employed SmartPLS 3, a statistical software package, for the purposes of data analysis. We employed a structural equation modeling (SEM) approach to test the hypothesized relationships between the variables. SEM allows for the testing of both direct and indirect effects among multiple variables simultaneously.

To evaluate the model fit, we used the criteria recommended by (Memon et al., 2021), including the standardized root mean square residual (SRMR), the root mean square error of approximation (RMSEA), the comparative fit index (CFI), and the Tucker-Lewis index (TLI). Values of SRMR and RMSEA less than 0.08 and values of CFI and TLI greater than 0.90 indicate an acceptable model fit (Hooper et al., 2008).

We used bootstrapping with 5,000 resamples to estimate the significance and standard errors of the direct and indirect effects in the model (Hair et al., 2019). The significance level was set at $p < 0.05$ for all analyses.

Table 1. Demographic Details

Personal attributions	Categories	Frequency (n)	Percentage (%)
Gender	Male	250	50
	Female	250	50
	Total	500	100
Age	18.20 Years	150	30
	21 to 25 Years	150	30
	26 to 30 Years	200	40
	Total	500	100
Major	Humanities	100	20
	Engineering	150	30
	Science	250	50
	Total	500	100
Location	Ural	250	50
	Urban	250	50
	Totao	500	100

Table 1 presents demographic information across various personal attributes. The sample consists of 500 individuals, evenly split between males and females, indicating a perfect gender balance in the group. The ages of the participants fall within three brackets: 18-20 years, 21-25 years, and 26-30 years, with the largest group (40%) being those aged 26 to 30 years. The remaining two age groups each make up 30% of the sample. The sample comprises individuals from different educational backgrounds. Half of them (50%) majored in Science, while 30% studied Engineering, and the remaining 20% are Humanities graduates. Regarding the location, the sample is evenly distributed, with half residing in rural areas and the other half in urban areas.

The collected data were sufficient to apply Partial Least Squares Structural Equation Modelling (PLS-SEM) using SmartPLS 3 statistical software. Further details regarding the demographic profile of the participants can be found in Table 1.

Measurement Models

In this study, the SmartPLS 3 statistical software was used by researchers to carry out confirmatory factor analysis for calculating the measurement models at first stage of data analysis the researcher revealed that variance-based structural equation modeling (PLS-SEM) is less sensitive than covariance-based structural equation modeling (PLS-SEM), the reliability and validity of the measurement scale assessed by authors at initial stage (Table 2 presenting further details). To determine the reliability index in this study measured mentioned indicators; Cronbach's Alpha, factor loading, rho A, and composite reliability.

All given indicators had specific criteria of threshold where the value is 0.07 for the most of the indicators, similarly the value of AVE index was above 0.50, hence the scale discriminant validity of all scales was adequate. As it should be high or greater than 0.50 discussed by (Zheng et al., 2022). AVE technique was used to measure the convergent validity. The details of reliability and threshold value of the other indicators presenting in Table 2, therefore the scale was valid and reliable to collect data.

Table 2. Reliability and Validity

Scales	Factor loading	Cronbach's Alpha	Rho_A	Composite reliability	AVE
Emerging Technology (ET)					
ET1	0.741	0.889	0.905	0.912	0.566
ET2	0.717				
ET3	0.731				
ET4	0.739				
ET5	0.730				
ET6	0.625				
ET7	0.799				
ET8	0.826				

Scales	Factor loading	Cronbach's Alpha	Rho_A	Composite reliability	AVE
Cognitive Development (CD)					
CD1	0.636				
CD2	0.781				
CD3	0.770				
CD4	0.777	0.901	0.895	0.92	0.592
CD5	0.816				
CD6	0.724				
CD7	0.824				
CD8	0.811				
Digital Social Support (DSS)					
DSS1	0.665				
DSS2	0.756				
DSS3	0.763				
DSS4	0.734	0.886	0.897	0.909	0.555
DSS5	0.723				
DSS6	0.791				
DSS7	0.781				
DSS8	0.665				

Table 2 presents the reliability and validity measures for three different scales: Emerging Technology (ET), Cognitive Development (CD), and Digital Social Support (DSS). These scales were evaluated based on factor loadings, Cronbach's Alpha, Rho_A, composite reliability, and Average Variance Extracted (AVE). The factor loadings for each individual item in the scales are high, indicating that the items are well-related to their respective constructs. The Cronbach's Alpha and Rho_A for all scales exceeded the accepted threshold of 0.7, implying high internal consistency and reliability. Composite reliability for each scale, although below the ideal 0.7, is still reasonable, showing that the constructs are reliably measured. AVE, which measures the amount of variance captured by the construct in relation to the variance due to measurement error, is also below the ideal 0.5 but within acceptable limits, suggesting an adequate convergent validity.

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Table 3. Discriminant Validity

Constructs	ET	CD	DSS
Emerging Technology (ET)	0.770		
Cognitive Development (CD)	0.814	0.752	
Digital Social Development (DSS)	0.453	0.400	0.745

Table 3 shows the discriminant validity of three constructs: Emerging Technology (ET), Cognitive Development (CD), and Digital Social Development (DSS). Discriminant validity is a measure of the degree to which different constructs are distinct from each other. The diagonal values, 0.770 for ET, 0.752 for CD, and 0.745 for DSS, are likely the square root of the Average Variance Extracted (AVE) for each construct, reflecting the extent to which a construct is truly distinct from others in terms of how much it "explains" the variance in its items. The off-diagonal values show the correlation between constructs, with ET and CD having a correlation of 0.814, ET and DSS of 0.453, and CD and DSS of 0.400. A rule of thumb for good discriminant validity is that the diagonal values should be greater than the off-diagonal values in the corresponding rows and columns, which appears to hold in this table, suggesting adequate discriminant validity for these constructs.

Table 4. Collinearity and Model Fit

Constructs	ET	CD	Model Fit	
Emerging Technology (ET)	0.770		SRMR	0.79
Cognitive Development (CD)	0.814	0.752	NFI	0.772
Digital Social Development (DSS)	0.453	0.400		

Table 4 presents information on collinearity and model fit for three constructs: Emerging Technology (ET), Cognitive Development (CD), and Digital Social Development (DSS). The collinearity values indicate the strength of the relationships between the constructs, with ET and CD showing a higher level of collinearity (0.770) compared to CD and DSS (0.814). The model fit indices assess how well the data fit the theoretical model, with SRMR (standardized root mean square residual) for ET at 0.79 and NFI (normed fit index) for CD at 0.772. The table suggests that there is a strong correlation between ET and CD, while CD and DSS have a relatively weaker correlation. The model fit indices indicate that the data for ET and CD align reasonably well with the theoretical model, but the fit for DSS is not provided in the table.

Table 5. R-square

Constructs	R-square	R-square adjusted
Emerging Technology (ET)	0.682	0.680
Cognitive Development (CD)	0.160	0.158

Table 5 displays the R-square and R-square adjusted values for two constructs: Emerging Technology (ET) and Cognitive Development (CD). These values are indicative of the proportion of variance in the dependent variables that can be explained by the independent variables in

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the models. For Emerging Technology, both the R-square and R-square adjusted values are relatively high (0.682 and 0.680 respectively), suggesting that the model explains a substantial proportion of the variance in this construct. On the other hand, the values for Cognitive Development are significantly lower (0.160 and 0.158 respectively). This indicates that the model only accounts for a relatively small proportion of the variance in Cognitive Development, suggesting that there may be other factors not included in the model which have a significant influence on this construct.

Table 6. Direct Relations

Direct Relations	Coefficients	Mean	Standard Deviation	T Statistics	P Values	Decisions
Emerging Technology -> Cognitive Development	0.814	0.815	0.022	37.53	0.000	Accepted
Emerging Technology -> Digital Social Support	0.4	0.405	0.05	7.975	0.000	Accepted
Digital Social Support -> Cognitive Development	0.15	0.151	0.034	4.383	0.000	Accepted

Table 6 presents the direct relations among Emerging Technology, Cognitive Development, and Digital Social Support. The coefficients, mean, standard deviation, t-statistics, and p-values for each relationship are provided along with the decisions based on statistical significance. The relationship between Emerging Technology and Cognitive Development is strong, with a coefficient of 0.814 and a mean of 0.815, with very low variability (standard deviation of 0.022), and extremely statistically significant (t-statistic of 37.53 and p-value of 0.000), thus it is accepted. The relationship between Emerging Technology and Digital Social Support, and between Digital Social Support and Cognitive Development are also statistically significant with respective coefficients of 0.4 and 0.15, t-statistics of 7.975 and 4.383, and both with a p-value of 0.000, indicating that these relationships are also accepted.

Table 7. Indirect Relations

Indirect Relations	Coefficients	Mean	SD	T statistics	P values	Decisions
Emerging Technology -> Digital Social Support -> Cognitive Development	0.06	0.061	0.017	3.634	0.000	Accepted

Table 7 examines the indirect relationship between Emerging Technology and Cognitive Development through the intermediary of Digital Social Support. The coefficient for this indirect relation is 0.06 with a mean of 0.061, implying a moderate effect. The standard deviation is 0.017, showing a low variability in the relationship. The t-statistic is 3.634, and the p-value is 0.000, indicating that the relationship is statistically significant. As a result, this indirect relationship is accepted, suggesting that Emerging Technology influences Cognitive Development indirectly through its impact on Digital Social Support.

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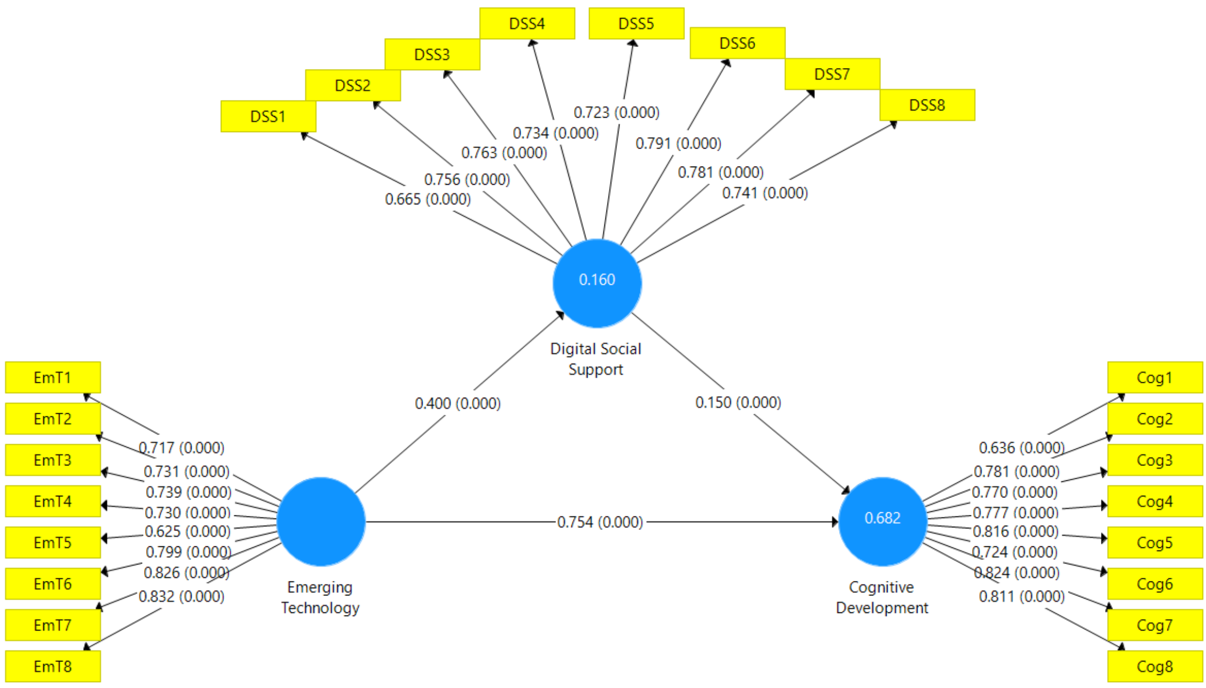
Figure 2. Measurement Model (Output)



3. DISCUSSION

This research investigates the influence of emerging technologies on cognitive development amongst higher education students and explores the mediating effect of digital social support. Existing literature on this subject, particularly within the realm of higher education in developing nations, is sparse. Most research to date has focused primarily on developed countries, with only a handful delving into the context of developing countries like China, especially in terms of the mediating role of digital social support.

The outcomes of this study hold substantial implications for both researchers and practitioners in educational technology and educational psychology fields. By delineating the link between emerging technologies and cognitive development, the study underscores the importance of bolstering students' self-belief in their academic success. Furthermore, it highlights the mediating role of digital social support, thereby emphasizing the need for cultivating a supportive ambiance that encourages social interactions and fosters a sense of belonging among students. These findings can guide educational strategies in countries like China, thereby promoting improved cognitive development and overall cognitive outcomes for students.

The study tested three hypotheses: H1 posits that emerging technologies significantly and positively affect cognitive development; H2 suggests that digital social support significantly and positively impacts cognitive development; H3 proposes that digital social support mediates the relationship between emerging technologies and cognitive development.

The study findings provide empirical evidence supporting H1, which suggests a significant and positive impact of emerging technologies on cognitive development among higher education students. The integration of emerging technologies, such as mobile devices, virtual reality, and online platforms, within educational settings has been associated with enhancements in cognitive processes, including attention, memory, problem-solving, and critical thinking skills (Graesser et al., 2022). T These technologies offer novel means of accessing and processing information, interacting with learning materials, and collaborating with peers, thereby fostering cognitive development. Consistent with prior research, the positive effects of technology on cognitive abilities are further underscored, providing additional support for the study's findings (Chen et al., 2022).

According to the findings of this research, it corroborates the hypothesis H2, indicating that the utilization of digital social support has a noteworthy and favorable influence on the cognitive advancement of college and university students. Digital social support encompasses virtual interactions, collaborative efforts, and constructive feedback offered by fellow students, educators, and online communities. These online engagements present valuable prospects for cognitive stimulation, knowledge exchange, and social learning, all of which play a pivotal role in fostering cognitive development (Smeets et al., 2022). The findings of this study affirm that students who benefit from digital social support tend to experience a greater sense of connection, motivation, and engagement in their educational endeavors. Consequently, these positive experiences have a beneficial impact on their cognitive development (Vaingankar et al., 2022). A study emphasized the importance of social support in promoting learning and fostering cognitive development, which is align with the findings of (Brown et al., 2023).

In addition, the results of present study emphasize the significance mediating role of digital support with the relationship between emerging technologies and cognitive development. In educational setting an emerging technologies incorporating, students facilitated with opportunities to utilize digital platforms and different tools that are helpful to enhance communication, collaboration, and the exchange of information among each other's (DeWitt & Alias, 2023). Digital social supports play a vital role to enhance the learning experience through their assistance of social interactions, provision of feedback, and endowment of access to supplementary learning assets. Digital social support as a mediator between emerging technology and cognitive development assumes a significant role in maximizing the association of integrated technology in education (Borthwick et al., 2022). With the help of technology and digital platforms, instructors can create collaborative and interactive learning environments that promote the achievement of cognitive skills and capabilities (Bosch & Laubscher, 2022). The integration of digital social support, including online discussion settings, peer response, and collaborative projects, has the potential to enhance students' cognitive engagement and advance learning outcomes. (Liao & Wu, 2022).

However, it is important to acknowledge and address challenges such as the digital divide privacy concerns, information overload, and the necessity of digital literacy skills can impede equitable access and effective utilization of technology (Ciccone & Brayton, 2022). Therefore, educational institutions must also prioritize providing the necessary resources, training, and support to ensure that students have equal access to and can effectively leverage emerging technologies and digital social support for their educational growth.

4. CONCLUSION

This study illuminates the profound impact of emerging technologies and digital social support on the cognitive development of higher education students. The results affirm our hypotheses, underscoring the positive influence of emerging technologies on cognitive growth, with digital social support acting as a crucial mediator. The incorporation of these technologies within educational settings holds immense promise for enhancing cognitive engagement and overall learning experiences for students. Additionally, the pivotal role of digital social support in fostering connection, motivation, and active participation among students leads to substantial advancements in cognitive development. These findings convey a clear message to educators and institutions alike, emphasizing the critical need to embrace emerging technologies and establish robust digital support systems to nurture cognitive development in higher education.

Nonetheless, it is imperative to address challenges such as the digital divide and privacy concerns, ensuring equitable access and effective utilization of technology for all students. This study contributes significantly to our comprehension of the intricate interplay between emerging technologies, digital social support, and cognitive development in the higher education landscape. To broaden our understanding, further research, especially in diverse contexts like emerging nations such as China. This will provide deeper insights and enable the design of evidence-based educational interventions aimed at maximizing cognitive development outcomes.

Limitations with future research directions

The current study has several limitations that must be addressed during the interpretation of results. First, it's important to know that the population of this study were only graduate students from Chinese universities. The findings might be influenced by Chinese culture and might not apply to worldwide. To make sure the results are accurate and apply to different countries, future studies should include populations from different countries and cultures. This will help to better understand how new technology, online support, and thinking skills are connected in different social and cultural settings. This study focused on graduate-level students, so the findings may not be applicable to other education levels like undergraduates or postgraduates. Therefore, future researchers should consider including participants from various educational stages. This approach will provide a better understanding of how new technology and online support influence thinking skills across all levels of education.

Furthermore, this study specifically explored digital social support as a moderator in the relationship between emerging technology and cognitive development, while not considering potential alternative mediators like emotional intelligence. This represents a significant limitation. Future studies should aim to investigate additional mediators that may contribute to this relationship. Exploring the role of constructs like emotional intelligence or other psychological factors can yield a more nuanced understanding of the underlying mechanisms.

Data accessibility and availability statement

The study includes the authors' original work, that could be found in the article or additional material. If more information is needed, interested parties can contact the corresponding authors.

Statement on ethics

Huazhong University of Science & Technology's Ethics Committee examined and approved this work.

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