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The Mediating Role of Cognitive Control and Flexibility on Load and Usability in Distance Education

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Abstract: The focus of this research is on the process of conducting distance education online, which is undergoing rapid transformation due to the impact of digitalization. The primary objective is to examine how cognitive load arising during online distance learning affects the perceived system usability, and the role of cognitive control and flexibility in this relationship. By revealing the direct and indirect effects of cognitive load, the study aims to contribute to the improvement of online education platforms in terms of user experience. The research was conducted on online courses taken by Akdeniz University students via the Microsoft Teams platform. Cognitive control and flexibility were measured using the Cognitive Control and Flexibility Scale, cognitive load was measured using the NASA-TLX, and the perceieved system usability was determined using the System Usability Scale. The findings show that, as cognitive load increases, perceived system usability decreases; conversely, this perception increases with higher cognitive control and flexibility. Furthermore, it was determined that cognitive load indirectly affects system usability via cognitive control and flexibility. Consequently, online education systems should be designed to reduce users' cognitive load while supporting their cognitive control and flexibility.

Index Terms: Distance Learning, Online Learning Platforms, Perceived System Usability, Cognitive Load, Cognitive Control and Flexibility.

1. Introduction

In the modern era, the rapid development of communication technologies has a profound effect on both individual and corporate life. The advent of sophisticated communication technologies has facilitated enhanced accessibility, thereby contributing to the efficiency of corporate operations [1]. This technological transformation has also led to significant changes in the field of education; educational processes have become more accessible and flexible through digitalization [2].

It is possible to posit that one of the most prominent and widespread consequences of this transformation are distance learning. The advent of technology has precipitated a marked increase in the global prevalence of distance learning [1]. While this model offers flexibility and accessibility to students, it also provides teachers with the opportunity to reach a wider audience. Nevertheless, distance learning has been shown to engender several detrimental effects. The challenges associated with this model include reduced social interaction among students, lack of motivation, and the digital divide [2].

It is evident that with the accelerating process of digitalization in recent years, the utilization of digital systems, which were previously regarded as sophisticated, has become pervasive in day-to-day life. Examples of such systems include credit cards, mobile banking applications, QR code menus and e-government services. The effective utilization of these systems is imperative for the enhancement of individuals' quality of life. However, it should be noted that

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usability is not solely contingent on technical adequacy; rather, it is also directly associated with users' cognitive processes [3].

The advent of the pandemic has precipitated this transformation, compelling educational institutions to expeditiously transition to distance learning systems [4]. Research indicates that the efficacy of online education is contingent on students' prior experience with computers [5]. It has been demonstrated that students with prior experience of computer use exhibit a higher level of proficiency in the utilization of these platforms, a phenomenon that can be attributed to a reduced cognitive load (CL). The findings of Al Ghalayini et al. [6] demonstrate a correlation between usability and CL, suggesting that as usability improves, CL decreases.

Sweller's [7] seminal Cognitive Load Theory (CLT) emphasizes the importance of the effective use of limited cognitive resources in learning processes. In this context, it is necessary to both increase usability and reduce users' CL in the design of online education platforms.

The primary objective of this study is to examine the direct effect of CL on users' perceived system usability (PSU) when using an online distance-learning platform, and the mediating role of cognitive control and flexibility (CCF) in this relationship. In this context, the study analyses how the CL experienced by users affects their PSU and whether this effect is indirectly shaped through CCF. In this respect, the research aims to contribute to the design of more user-friendly online education systems and to reveal the mediating role of CCF, a role that is lacking in literature.

2. Literature Review

2.1. Human-Computer Interaction and Usability

Human-computer interaction (HCI) is an interdisciplinary field examining how users interact with computer systems, as well as the experience arising from this interaction. According to Norman (1988), the mental models that users develop during their interactions with the system determine how understandable and predictable the system design is. Shneiderman et al. [3] emphasize that HCI design principles should be structured to reduce cognitive demand on users. They note that well-designed interfaces facilitate interaction and improve the user experience.

Usability refers to a system's ability to be used effectively, efficiently and satisfactorily by users [8]. The ISO 9241-11 standard defines usability in terms of effectiveness, efficiency and satisfaction. It focuses on criteria such as the extent to which users can achieve their goals, the resources involved and their satisfaction with the process. Dumas and Redish [9] define usability as the extent to which users can easily and quickly accomplish their goals, while Benyon et al. [10] and Kanis [11] argue that ease of use and accessibility directly impact the perception of quality.

In this context, the user-friendliness of distance learning platforms – offering an open navigation structure, consistent feedback, and clear task flows – has been shown to reduce CL and increase perceived usability [12,13,14]. It is evident that the concepts of IBE and usability are intrinsically linked to cognitive processes and thus serve as the fundamental foundation for the research model.

2.2 Perceived System Usability (PSU)

The term "perceived system usability" refers to users' subjective assessments of how easy, understandable, functional, and reliable a system. Norman [15] emphasizes the notion that perceived usability is more closely associated with the representation in the user's mind than with the actual performance of a system. This observation indicates that user experience cannot be considered independently of design. In a similar vein, Krug [16] posits that the extent to which users can navigate a system without conscious thought serves as a crucial metric for evaluating the effectiveness of interface design.

As the user's level of knowledge about the system increases, it becomes possible for them to understand the system's operating logic and perform tasks with less effort; in this case, perceived usability and the system's actual usability converge [3]. Within the paradigm of distance education, the user-friendliness of the system is a pivotal factor in determining its efficacy. This encompasses a range of processes, including the accessibility of course content, the availability of materials, the functionality of assignment submission, and the ease of communication with teaching staff. The utilization of High PSU facilitates students' engagement with the platform, thereby enhancing their participation in the learning process.

2.3. Cognitive Load (CL)

CL theory highlights the limited capacity of an individual's working memory during learning and problem-solving processes. Sweller [7] proposed a taxonomy of CL, distinguishing between three categories: intrinsic, extrinsic, and germane load. Chandler and Sweller [17] propose that intrinsic load is associated with the complexity of the information to be learned and the interaction of its elements; in contrast, extrinsic load is related to unnecessary mental demands arising from the presentation format of the material. In contrast, Germane load is defined as meaningful cognitive effort that supports learning.

Within digital learning environments, the presence of complex menu structures, cluttered screen layouts, redundant visual elements, and inadequate instructions can collectively contribute to an increase in extraneous CL. This, in turn,

can lead to difficulties for students in maintaining focus on the learning material. Multidimensional scales such as NASA-TLX are widely utilized to assess CL through dimensions such as mental effort, time pressure, and performance perception. Increased CL has been demonstrated to cause strain on the capacity of working memory, higher error rates, and slower information processing [7,18]. Consequently, the reduction of design-related load in distance learning platforms is imperative for enhancing learner performance and optimizing the quality of interaction with the system.

2.4. The Relationship between CL and PSU

The relationship between CL and PSU is directly linked to the cognitive demands of user interfaces. In circumstances where CL is elevated, users encounter greater challenges in comprehending and executing tasks within the system. This experience results in a perception of diminished system usability. Sweller's [7] emphasis on the limitations of working memory demonstrates that design-related unnecessary information density has the capacity to reduce user performance and negatively affect learning processes.

As stated by Nielsen [8], unnecessary complexity and poor information architecture have been demonstrated to prolong task completion time, increase error rates, and reduce satisfaction. The combination of such negativity with an augmented external CL has been demonstrated to result in a decline in PSU. In the context of distance learning, students have reported that the system is perceived as "challenging" when confronted with complex interfaces or inadequate instructions, particularly in activities such as accessing course content, uploading assignments/projects, and participating in synchronous/asynchronous activities on learning platforms [13,14]. This perception is influenced by the complexity of the interface and the comprehensibility of the instructions, which collectively impact the students' overall PSU.

Consequently, an increase in CL results in a decrease in PSU, given its impact on both cognitive performance and the subjective evaluation of the system. In this context, the CL → PSU pathway is supported by both theoretical and empirical evidence.

2.5. The Mediating Role of CCF

The theoretical framework of this study relies on the integration of Cognitive Load Theory (CLT) [19] and the Executive Functions Framework [20]. While CLT posits that the limited capacity of working memory determines the efficiency of instructional interactions, the Executive Functions Framework defines the regulatory mechanisms—specifically cognitive flexibility and inhibitory control—required to manage these cognitive resources under high-demand conditions. Theoretically, these constructs are operationalized through the "Resource Depletion Hypothesis", which suggests that excessive extrinsic cognitive load not only occupies working memory but also depletes the mental energy required for effective cognitive control [21]. Consequently, when learners' cognitive resources are overwhelmed by interface demands, their capacity for flexibility diminishes, directly degrading their perceived system usability. This study integrates these perspectives to posit that CCF acts as a dynamic regulatory resource bridging the gap between interface demands (load) and user experience (usability).

The selection of CCF as the central mediator in this study, rather than affective constructs such as computer anxiety or motivation, is grounded in the "shared resource necessity" of information processing. Unlike affective variables that influence performance indirectly, CCF and working memory compete directly for the same limited neural substrates in the prefrontal cortex [22]. Therefore, CCF represents the primary cognitive bottleneck where the impact of extrinsic load is first manifested before it cascades into behavioral outcomes like perceived usability. This makes CCF a more proximal and theoretically precise mediator for explaining the cognitive mechanics of user experience in high-load environments. Cognitive control refers to an individual's capacity to manage their attention, reevaluate their thoughts, and regulate their goal-directed behaviors [23]. Cognitive flexibility is defined as the ability to adapt to changing conditions, develop alternative solutions, and switch between different perspectives [20]. Diamond [24] identifies these two structures as fundamental components of executive functions and suggests that individuals with high levels of CCF are more successful in coping with complex tasks.

The emphasis of CL theory on the management of mental resources explains why CCF are critical in the context of distance education. In situations of excessive CL, there is a demonstrable decline in the effectiveness of executive functions. This decline is accompanied by impairments in the maintenance of attention, the processes of planning and problem-solving [24]. In such cases, individuals may encounter difficulties in adapting to unexpected situations they encounter on digital platforms and may be unable to develop alternative strategies.

In the study conducted by Martins et al. [25], it was observed that individuals who demonstrated high levels of cognitive flexibility exhibited superior performance in their interactions with digital systems. They also demonstrated a faster rate of task completion and a more positive evaluation of their experience. These findings suggest that CCF may have a positive effect on PSU. Conversely, the weakening of CCF by high CL suggests that the negative effect of CL on PSU is partially mediated through CCF.

In this context, it is theoretically meaningful for CCF to play a mediating role in the relationship between CL and PSU: increased CL weakens executive functions, lowering the level of CCF; while low CCF negatively affects PSU by limiting users' capacity to manage the system, adapt to problems, and perform tasks effectively [20,23,25].

Consequently, the CL → CCF → PSU pathway offers a significant and comprehensive theoretical model at the intersection of executive functions and CLT.

3. Methodology

The present study employed a quantitative research method. The primary objective of the present study was to examine the effect of CL on PSU and to evaluate the mediating role of CCF in this effect. The following section provides a comprehensive description of the research model, hypotheses, sample, data collection process, and measurement tools used.

The structural model constructed in the study assumes that CL directly affects users' PSU; however, this relationship can also be indirectly shaped through individuals' levels of CCF capacities. In this context, CCF were considered as mediating variables in the analysis of indirect effects between CL and PSU.

The PROCESS macro (Model 4), developed by Hayes [26], was utilized in the analysis of the data. This approach constitutes a contemporary methodology that generates more robust outcomes in comparison to the classic mediation test proposed by Baron and Kenny [27]. The utilization of the bootstrap method facilitates the estimation of confidence intervals, thereby enabling the assessment of the significance of the mediation effect. In the study, 5,000 bootstrap samples were taken, and direct, indirect, and total effects were calculated at a 95% confidence level. In instances where the confidence interval of the indirect effect did not include zero, the mediating effect was regarded as statistically significant.

This analytical approach is of particular significance, as it considers the non-linear nature of complex interactions between cognitive processes. This is because CL does not determine perceived usability in isolation; this effect may vary depending on the user's capacity to manage control processes and adapt to environmental changes (i.e., CCF). Consequently, mediation analysis facilitates the statistical identification of this indirect effect mechanism (i.e. causal pathways) [26, 28].

3.1. Research Model and Hypotheses

The study examined CL as the independent variable, PSU as the dependent variable, and CCF as the mediating variable. The relationships between these variables were tested within the framework of a mediation model. The hypotheses formulated for the study are outlined as follows:

H_1: CL has a negative effect on PSU.
H_2: CCF has a positive effect on PSU.
H_3: CCF plays a mediating role in the relationship between CL and PSU.

The research model diagram (Figure 1) forms the basis for testing the hypotheses in the study.

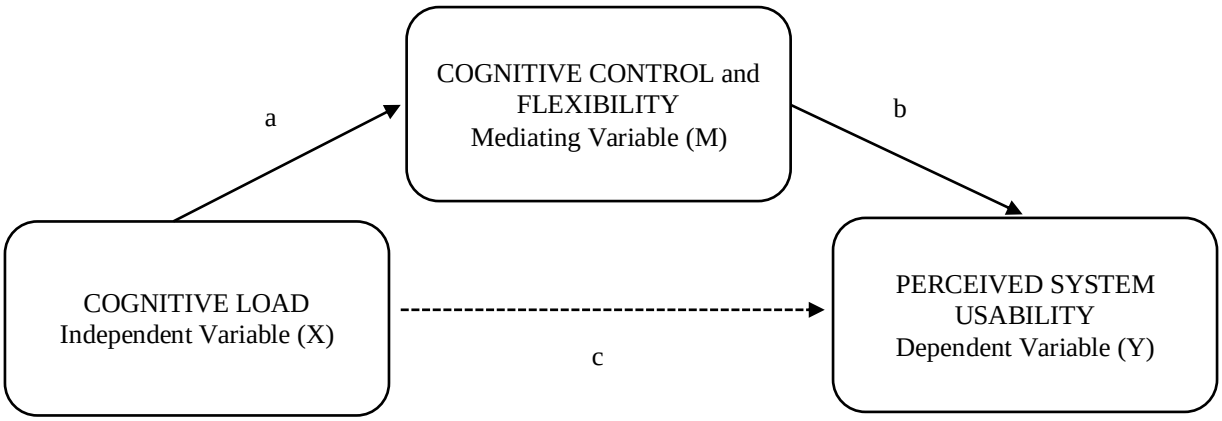


Fig. 1. Research Model.

3.2. Population and Sample

The population of the study consists of students who participated in online courses via the Microsoft Teams platform at Akdeniz University during the 2022–2023 academic year. Convenience sampling, a non-probability sampling method, was employed in the study. In this context, data was collected from students who regularly participated in online courses.

The adequacy of the sample size (N=263) was rigorously evaluated based on statistical power requirements specifically for mediation analysis. According to Fritz and MacKinnon [29], a sample size ranging between 148 and

400 is required to detect small-to-medium indirect effects with 0.80 statistical power using bias-corrected bootstrapping. Furthermore, the current sample size satisfies the multivariate data analysis criterion suggested by Hair et al. [30], which recommends a minimum participant-to-item ratio of 5:1. With 33 items in the survey, the study exceeds this threshold, ensuring sufficient statistical power to validate the proposed mediation model and minimize Type II errors.

Furthermore, the research design employed a homogeneous sampling strategy to minimize the confounding effects of extraneous variables. By restricting the participant pool to active university students (89.7% aged 18–25), the study effectively controlled for age-related variations in cognitive processing speed [31]. Additionally, since all participants were regular users of the same institutional learning management system (Microsoft Teams) for their curricular activities, the variance associated with "platform novelty" and varying levels of prior digital literacy was naturally suppressed, ensuring that the measured cognitive load was primarily attributed to the task and system design rather than individual lack of familiarity [32].

3.3. Data Collection Tools

Three different scales were used in the study:

- CCF Scale: The scale developed by Gabrys et al. [23] and adapted into Turkish by Demirtaş [20] was utilized. The scale comprises 19 items, designed to assess individuals' levels of cognitive control. The following examples are provided to demonstrate the range of the subject:
  - "I feel like I'm losing control over my thoughts and feelings."
  - "I try to think of different solutions before taking action to best cope with the situation."
- CL Scale (NASA-TLX): The scale in question was developed by Hart and Staveland [33] in 1988. It is a tool designed to measure multidimensional workload, incorporating a number of factors including mental load, physical load, time pressure, performance, effort, and frustration. The scale is a measurement tool consisting of six items, each with a 21-point Likert-type rating scale. The following sample items are provided for your consideration:
  - "How mentally challenging was the task?"
  - were you in accomplishing what was asked of you?"
- System Usability Scale (SUS): The scale developed by Brooke [34] assesses users' PSU. It is a 10-item, 5-point Likert-type scale. Sample items include:
  - "I think I will need the support of someone more technical to be able to use this system."
  - "I think many people will learn how to use this system very quickly."

3.4. Data Collection Process

The collection of data was achieved through the implementation of an electronic survey instrument administered to students participating in online classes via the Microsoft Teams platform. Participants were requested to take part in the study voluntarily, and the guarantee of anonymity was provided. The participation process was conducted in accordance with established ethical principles, and all requisite permissions were obtained.

3.5. Data Analysis

The data obtained was analyzed using the SPSS software package. In the analysis process, the Hayes' PROCESS macro was utilized to examine the direct and indirect relationships between variables. In this context, the bootstrap method was used to assess the mediating effect, and confidence intervals were derived using 5000 resampling to ascertain the statistical significance of the findings.

3.6. Ethical Considerations

Prior to data collection, all participants were presented with an electronic Informed Consent Form detailing the study's objectives, the voluntary nature of participation, and the strict confidentiality of their responses. Participants explicitly confirmed their consent to participate, understanding that the collected data would be anonymized and used exclusively for scientific research purposes. The entire research process was conducted in full compliance with the ethical principles outlined in the Declaration of Helsinki [35]. The participation of students in the research was voluntary, personal data confidentiality was maintained, and approval was obtained from the Akdeniz University Social and Human Sciences Ethics Committee (Board Decision No. 247 dated April 22, 2025).

4. Results and Discussion

In this section, an analysis of data obtained from students participating in the study is presented. The findings are given under the headings of descriptive statistics, correlation analyses, regression analyses, and mediation analyses.

4.1. Descriptive Statistics

The demographic characteristics of the students participating in the study (age, grade level, gender) are presented in Tables 1-3.

Table 1. Sample Distribution by Age Variable.

Variable	Category	f	%
Age	18-25	236	89.7
	26-36	16	6.2
	37-55	11	4.3
Total		263	100

A close examination of the age distribution of the total 263 participants in the study reveals that the vast majority fall within the 18–25 age range (89.7%). This finding suggests that the sample is predominantly composed of young adults. The age demographic of the participants was as follows: 6.2% fell within the 26–36 age range, while 4.3% were between the ages of 37 and 55. Consequently, the participant profile of the study consists predominantly of young individuals, indicating that the study reflects the views and experiences of individuals in their university years or early career stages.

Table 2. Sample Distribution by Grade-level.

Variable	Category	f	%
Grade	1	31	11.8
	2	108	41.1
	3	50	19.0
	4	57	21.7
	Master's	10	3.8
	PhD.	7	2.7
Total		263	100

An investigation into the distribution of 263 study participants according to their grade level reveals that the highest percentage, amounting to 41.1%, is comprised of second-grade students. The demographic composition of the sample is as follows: 21.7% of the participants are in 4th grade, 19% are in 3rd grade, and 11.8% are in 1st grade. At the graduate level, 3.8% of the participants were enrolled in master's programs, while 2.7% were pursuing doctoral degrees. These findings suggest that the study was predominantly conducted among undergraduate students, with a limited participation of graduate students.

Table 3. Sample Distribution by Gender.

Variable	Category	f	%
Gender	Female	161	61.2
	Male	102	38.8
Total		263	100

A further analysis of the gender distribution of the total 263 participants in the study reveals that 61.2% of the participants are female and 38.8% are male. This finding suggests that female participants exhibited a greater level of interest in the study compared to their male counterparts.

4.2. Normality and Reliability Analyses

The validity and reliability levels of the scales utilized in the study, as well as the distribution characteristics of the variables, were subjected to detailed analysis. Initially, an examination of descriptive statistics and normality indicators for the CCF, CL, and PSU variables was conducted.

As demonstrated in Table 4, the skewness value of the PSU variable is -0.302, the kurtosis value is -0.033; the skewness value of the CL variable is -0.058, the kurtosis value is -0.545; the skewness value of the CF variable is -1.619, and the kurtosis value is 2.405. In consideration of the ±1 range suggested by George and Mallery [36] and the ±3 range proposed by Kline (2011), it was ascertained that the distributions of the PSU and CL variables can be regarded as normal, while the CCF variable exhibits a partial deviation from normality within acceptable limits.

Table 4. Descriptive Statistics and Normality Indicators for PSU, CL, and CCF Variables.

	N	*Min*	*Max*	*Mean*	*SS*	*Skewness*	*Kurtosis*
PSU	263	5.00	100.00	65.29	17.75	-0.302	-0.033
CCF	263	1.83	6.50	5.45	0.90	-1.619	2.405
CL	263	1.50	20.67	12.06	4.53	-0.058	-0.545

The Kolmogorov-Smirnov and Shapiro-Wilk tests were employed to assess the assumption of normality. According to the results of the Shapiro-Wilk test, the p-values of the PSU and CCF variables are below .05, while the p-value of the CL variable is above the .05 level. Accordingly, although the distribution of the CCF variable is not perfectly normal, the high sample size (n = 263) and the skewness-kurtosis values within the ±3 limits provide sufficient conditions for parametric analyses (Razali and Wah, 2011; Kim, 2013). In summary, while there is a slight deviation from normality in the data, the distributions are generally deemed suitable for parametric analyses.

The reliability of the scales utilized in the study was ascertained through the implementation of Cronbach's Alpha coefficients. The alpha coefficients (α) for the CCF, System Usability Scale, and NASA-TLX CL Scale were reported as 0.85, 0.84, and 0.87, respectively. These values indicate that all scales have high internal consistency (Nunnally and Bernstein, 1994).

4.3. Confirmatory Factor Analysis

Confirmatory factor analysis, a robust statistical technique, is utilized to ascertain the compatibility of a measurement model with its theoretical structure [37]. In this analysis, the extent to which variables align with a predefined factor structure is evaluated, and the model's fit to the observed data is tested using various fit indices. CFA has gained significant popularity, particularly within the fields of psychometrics and behavioral sciences, for its role in validating scale validity. The following table presents the findings of the confirmatory factor analysis of the research model.

Table 5. Findings of the Validity Analysis for the Model.

	χ^2/df	CFI	TLI	RMSEA	SRMR	CR
Model	1,214	0,946	0,942	0,029	0,056	0,93

As can be seen from the data in Table 5, the model demonstrated an excellent overall fit, as indicated by the χ^2/df ratio below the recommended threshold and by CFI and TLI values approaching .95. Furthermore, the low RMSEA and SRMR coefficients, together with a high composite reliability score, provide strong evidence for the model's validity and internal consistency.

4.4. Correlation Analyses

In this section, correlation analysis was performed to determine the direction and strength of the relationships between variables. The objective of this analysis is to identify the significant relationships between variables such as CCF, CL, and PSU, as addressed in the study. This analysis aims to elucidate the manner in which these variables within the model interact with each other. Consequently, the levels of relationships between variables to be used in subsequent analyses (e.g., mediation tests) have been evaluated in advance. The correlation results are presented in Table 6.

Table 6. Pearson Correlation Results between PSU and CL.

	PSU	CCF	CL
PSU	-		
CCF	0.486***	-	
CL	-0.578***	-0.306***	-

A substantial negative correlation has been identified between CL and PSU ($r = -0.45$, $p < .01$). This finding suggests that as the CL experienced by students rises, they perceive the system as increasingly unusable. A significant positive correlation was identified between CCF and PSU ($r = 0.52$, $p < .01$). This finding suggests that as students' CCF levels increase, they evaluate the system as more usable. A considerable negative correlation has been identified between CL and CCF ($r = -0.38$, $p < .01$). Consequently, as students experience an increase in their CL, their CCF levels demonstrate a corresponding decrease.

4.5. Mediation Model

The study tests the mediating role of CCF on the effect of CL on PSU, through the mediating roles of CCF. Model 4, which was developed within the framework of Hayes' proposed PROCESS macro, facilitates the concurrent and comprehensive examination of direct and indirect effects between variables. This capability enables the assessment of the significance of causal paths through the utilization of bootstrap confidence intervals.

4.6. First Regression Model (CL → CCF)

The first stage of the mediation analysis examined the effect of CL on CCF. According to the regression analysis conducted in accordance with Hayes' PROCESS Model 4 approach, the model has meaningful explanatory power.

Table 7. Mediation analysis examined the effect of CL on CCF.

Variable	B	SE	t	LLCI	ULCI	p	R	R^2	F
Constant	6.1833	0.1511	40.919	5.886	6.481	< .001	.306	.094	26.946
CL	-0.0609	0.0117	-5.191	-0.084	-0.038	< .001			

According to Table 7, CL has a negative and significant effect on CCF (B = -0.0609, t = -5.1910, p < .001). This finding indicates that as CL increases, individuals' control and flexibility skills, which are evaluated within the scope of executive functions, decrease. The model's R^2value is .0936, meaning CL explains about 9.4% of the variance in CCF. While this ratio is considered to have low to moderate explanatory power in the social sciences, it represents a meaningful psychological effect, which is consistent with the predictions of CL theory [7]. This result aligns with literature suggesting that high CL can negatively affect one's ability to organize thoughts, sustain attention, and adapt to changing conditions.

4.7. Second Regression Model (CL and CCF → PSU)

The second stage of the mediation analysis examined the simultaneous effects of CL and CCF on PSU. Conducted in line with the multivariate regression approach proposed by Hayes (2018), the analysis shows that the model has meaningful, strong explanatory power (R^2= .4481). The findings of this analysis are presented in Table 8.

Table 8. Mediation analysis examined the simultaneous effects of CL and CCF on PSU.

Variable	B	SE	t	LLCI	ULCI	p	R	R^2	F
Constant	51.968	6.325	8.217	39.515	64.422	< .001	.669	.448	105.539
CL	-1.894	0.189	-10.000	-2.267	-1.521	< .001			
CCF	6.636	0.951	6.975	4.762	8.509	< .001			

The findings indicate that CL exerts a negative effect on PSU (B = -1.8938, p < .001), whereas CCF demonstrates a Positive and significant effect on PSU (B = 6.6356, p < .001). This finding aligns with prior research suggesting that elevated CL leads to diminished perceived usability (Sweller, 1988; Norman, 1988; Al-Ghalayini et al., 2020). Conversely, the findings that CCF, which are critical components of executive functions, enhance user experience are in alignment with the extant literature (Diamond, 2013; Martins et al., 2022). The model demonstrates that PSU is influenced by both cognitive strain and users' cognitive regulation capacity.

4.8. Total Effect (CL → PSU)

In the third stage of the mediation analysis, the total effect of CL on PSU was evaluated. The model under consideration includes only the CL variable, and the effects are tested without controlling for any mediating variables. The findings of the model are presented in Table 9.

Table 9. The total effect of CL on PSU.

Variable	B	SE	t	LLCI	ULCI	p	R	R^2	F
Constant	92.998	2.526	36.822	88.025	97.972	< .001	.587	.345	137.355
CL	-2.298	0.196	-11.720	-2.684	-1.912	< .001			

The findings of the analysis suggest a significant negative overall impact of CL on PSU, with a statistical significance of p < .001 and a coefficient of determination (R^2) of 0.99. This finding aligns with the notion of CLT, which suggests that an increase in CL can hinder user performance and affect perceptual evaluations [7,18]. This finding aligns with previous research that has demonstrated a negative correlation between high mental demands and perceived usability [6,15]. The model's R^2value of .3448 indicates that approximately one-third of the variance in PSU is explained by CL.

4.9. Indirect Effect (Bootstrap Results)

In the fourth stage of the mediation analysis, the indirect effect of CL on PSU was assessed through CCF. As outlined in Hayes' (2018) PROCESS Model 4 approach, for the indirect effect to be considered statistically significant, the bootstrap confidence interval must not include zero. The present study utilizes 5,000 bootstrap resamples, thereby demonstrating the statistical significance of the mediation mechanism.

Table 10. The indirect effect of CL on PSU through CCF.

Type of Effect	Constant (B)	SE	t	p	95% BCa GA	Stand. β	Comment
Total Effect (CL → PSU)	-2.298	0.196	-11.720	< .001	[-2.684, -1.912]	-0.587	Significant, strong negative total effect
Direct Effect (CL → PSU)	-1.894	0.189	-10.000	< .001	[-2.267, -1.521]	-0.484	Direct effect remains significant,

							partial mediation
Indirect Effect (CL → CCF → PSU)	-0.404	0.096	—	—	[-0.600, -0.231]	-0.103	Significant indirect effect, partial mediation

As shown in Table 10, the findings of the analysis indicate that CL's indirect effect on PSU via CCF is negative and significant (B = -0.4041, BootSE = 0.0963). The obtained 95% bias-corrected bootstrap confidence interval is [-0.5997, -0.2312] and does not include zero. This result suggests that CCF plays a partial mediating role in the relationship between CL and PSU. Consequently, an increase in CL corresponds to a decrease in CCF, which in turn contributes to a reduction in PSU. This finding aligns with the extant literature, which demonstrates that executive functions play a critical regulatory role in cognitive processes [24,38].

The standardized indirect effect (β = -0.1033) is significant, indicating that the indirect effect constitutes a substantial portion of the model's total effect. The magnitude of the mediating effect can be considered small to medium [39,40]. To further contextualize this finding, the ratio of the indirect effect to the total effect was calculated (P_M = .175). This indicates that approximately 17.5% of the deleterious impact of cognitive load on system usability is not a direct consequence of interface complexity but is rather transmitted through the depletion of the user's cognitive control and flexibility. While the standardized coefficient (β = -0.1033) corresponds to a "small" effect size according to Cohen [41], conventional benchmarks, in the context of user experience, this represents a practically significant "hidden cost". It implies that even minor increases in cognitive load can trigger a disproportionate decline in usability by compromising the learner's executive capacity, a phenomenon that has cumulative negative effects on long-term learning engagement. Moreover, the difference between CL's total effect (B = -2.2979) and direct effect (B = -1.8938) on PSU further underscores the significance of the indirect effect in the model. This discrepancy suggests that CL's impact on PSU is not solely attributed to cognitive strain but also encompasses an individual's capacity for control and flexibility.

This finding points to the multidimensional nature of the cognitive processes that shape user experience, particularly in online educational environments. CLT posits that an individual's performance will decline when their limited mental capacity is overwhelmed by excessive demands [7,18]. However, the mediating relationship revealed in this study demonstrates that an augmented CL exerts a negative influence on usability, and that the deterioration of executive functions under such loads further exacerbates this effect. In this context, the mediating role of CCF offers an important theoretical and practical contribution.

In summary, the impact of CL on PSU is articulated through both direct and indirect mechanisms. This underscores the necessity to deliberate design principles that mitigate CL and foster CCF and adaptability in the conception of distance learning platforms. Specifically, interface designs that provide guidance to the user, the simplification of task steps, the strengthening of feedback mechanisms, and content designs that support attention management have the potential to positively influence the mediation mechanism and increase system usability.

4.10. Findings Regarding Model Fit and Evaluation of Results

When all findings related to the mediation analysis are evaluated collectively, the model demonstrates a statistically significant fit. The substantial negative effect obtained on the CL → CCF path indicates that an increase in CL weakens executive functions. This finding is consistent with studies in the literature that emphasize the limitations of cognitive capacity [7,24]. When evaluating the simultaneous effects of CL and CCF on PSU, the model explains 44.8% of the total variance, which corresponds to a high level of fit in the social sciences [42]. The bootstrap results indicate that the indirect effect is significant, thereby demonstrating that the mediation mechanism is statistically robust [26,28]. The presence of both direct and indirect effects as being significant indicates that the model has a partial mediation structure and confirms that CCF processes play a critical role in usability evaluations. These results indicate that the measurement model employed functions in accordance with theoretical predictions.

To verify the robustness of the mediation findings across different methodological approaches, a supplementary Sobel test was conducted. The results (Z = -4.18, $p < .001$) were fully consistent with the bootstrap analysis, confirming that the indirect effect remains significant even under the strict assumptions of normal theory [43]. Additionally, collinearity diagnostics were examined to ensure the stability of the regression estimates; Variance Inflation Factor (VIF) values for all predictors were found to be well below the threshold of 3, indicating that the model is robust against multicollinearity bias [30].

5. Discussion and Conclusion

This study systematically investigates the impact of students' perceived CL on their PSU within the framework of distance education. Additionally, it explores the mediating role of CCF in this relationship. The data obtained from university students participating in classes in the Microsoft Teams environment present results consistent with both the theoretical framework and previous empirical findings. In addition, the data provide unique contributions to the mediation mechanism, which has been addressed only to a limited extent in the literature.

5.1. The Relationship between CL and PSU

The findings indicate that CL exerts a substantial negative effect on PSU. It was determined that as the CL experienced by students increased, they perceived the system as less usable. This outcome aligns directly with Sweller's [7] CLT, which posits that the complexity of a task directly correlates with the effort required to complete it. In circumstances where cognitive resources are scarce, the complexity of the user interface has been demonstrated to increase mental effort and reduce performance. These findings are consistent with those of studies examining the usability–CL relationship, as evidenced by Al-Ghalayini et al. [6].

The model's high explanatory power ($R^2 = .3448$) substantiates the hypothesis that CL is a fundamental determinant of perceived usability. In the context of distance learning, various factors have been identified as contributing to challenges experienced by students. These include navigation difficulties, the complexity of the content, time constraints, and technical issues. These challenges have been shown to result in an increase in CL, which, in turn, has a negative impact on perceived usability.

Critically, interpreting the negative impact of CL on PSU requires distinguishing between the sources of cognitive load. Sweller [19] differentiates between "intrinsic load" (inherent task complexity) and "extraneous load" (load induced by instructional design or interface). In this study, since the curriculum and learning content were standardized for all participants, the intrinsic load can be considered relatively constant. Therefore, the observed negative correlation is primarily attributed to "extraneous cognitive load" stemming from interface constraints, navigational complexity, or suboptimal information presentation within the platform, rather than the difficulty of the subject matter itself [44]. This distinction confirms that the decline in perceived usability is driven by design-related cognitive costs rather than curricular difficulty.

5.2. The Effect of CCF

The second key finding of the study is that CCF have a significant and positive effect on PSU. Individuals with high levels of CCF have been shown to possess enhanced attention maintenance, adaptation to changing conditions, and problem-solving skills. Consequently, these individuals tend to find it more manageable to navigate the demands posed by online platforms and to assess the system as more user-friendly.

This finding aligns with the conclusions of Diamond [24], who asserts that executive functions play a critical role in cognitive processes, and Martins et al. [25], who demonstrate that cognitive flexibility affects the user experience in digital learning environments. The increase in the variance explained by the model ($R^2 = .4481$) indicates that CCF makes a significant contribution to explaining PSU.

5.3. The Role of Mediation

The most original finding of the study is that CCF play a partial mediation role in the relationship between CL and PSU. Bootstrap analysis indicated that the indirect effect was significant ($B = –0.4041$; $\beta = –0.1033$) and that the 95% confidence interval did not include zero. This finding suggests that the mediating mechanism exhibits statistical significance [26,39].

This finding corroborates the following mechanism:

- As CL increases, CCF decreases.
- Conversely, as CCF decreases, PSU is found to be negatively impacted.
- Consequently, a portion of the CL → PSU relationship functions through CCF.

This finding contributes substantially to the concept of "executive function mediation," a concept that has been the subject of only a limited amount of research in the field of distance education. Despite the frequent examination of the CL–PSU relationship in the extant literature, its regulation by CCF has received only limited attention until now.

Furthermore, it is crucial to interpret these correlations within the specific temporal dynamics of the learning environment. The study was conducted on Microsoft Teams, a platform predominantly used for synchronous (live) instruction, which imposes inherent "temporal cognitive pressure" due to the continuous and transient nature of information flow [45]. This real-time demand likely amplifies the negative relationship between CL and CCF, as learners must exert greater executive effort to process stimuli without the option to pause or review. Consequently, the strength of this mediation mechanism might be attenuated in asynchronous (self-paced) environments where learners possess greater autonomy over their processing speed, thereby reducing the immediate tax on their executive functions.

5.4. Theoretical Contributions

The present study;

- proposes a novel mediating mechanism for the field of usability research by means of a comprehensive model that assesses the CL–CCF–PSU relationship.

- offers substantial empirical evidence that lends credence to the notion that executive functions play a pivotal role in the context of digital learning environments.
- demonstrates that the CLT in distance education operates not only through design flaws that increase load, but also through the individual's cognitive regulation capacity.

5.5. Practical Contributions

- It is imperative to employ design principles such as simplifying user interfaces, streamlining information architecture, and reducing task steps to minimize CL.
- Teaching strategies that support students' attention management, cognitive flexibility, and self-regulation skills should be utilized. These strategies may include short videos, illustrated explanations, progress cues, and feedback mechanisms.
- It is critical to ensure that course materials are meticulously structured into modular and manageable segments, thereby fostering students' cognitive control capacity.

5.6. Limitations and Directions for Future Research

First, the sample was drawn exclusively from undergraduate students at a specific public university in Turkey, utilizing a convenience sampling method. While this homogeneity allowed for the control of confounding variables related to institutional infrastructure and instructional delivery [46], it inevitably restricts the ecological validity and generalizability of the findings to broader populations with diverse demographic profiles. Consequently, the reported mediation effects should be interpreted strictly within this specific institutional context, and caution should be exercised when extrapolating these results to other cultural or educational settings [47].

Second, the utilization of non-probability convenience sampling inevitably introduces potential selection bias, as participation was contingent upon students' willingness and availability rather than random selection. This lack of randomization restricts the statistical representativeness of the sample, implying that the findings may disproportionately reflect the perspectives of students with higher technology engagement or motivation, rather than the broader student population [48].

Third, the operationalization of cognitive load relied exclusively on the NASA-TLX, a subjective self-report instrument administered post-task. While this scale provides a reliable index of perceived workload, it reflects a retrospective evaluation and may not fully capture the real-time, momentary fluctuations in cognitive processing that occur during dynamic online learning tasks [49]. Consequently, the reported load represents the students' conscious awareness of difficulty rather than the immediate neural cost. Future research could overcome this limitation by triangulating self-report data with objective, continuous physiological measures such as eye-tracking, pupillometry, or EEG to provide a more granular analysis of cognitive strain [50].

Finally, while this study elucidates the mediating mechanism of CCF, it does not explore the boundary conditions that might influence this process. The relationship between cognitive load and usability is likely not uniform across all contexts; it may be moderated by factors such as task complexity (e.g., passive listening vs. active problem-solving) or platform modality (e.g., mobile vs. desktop). Therefore, future research should adopt a "moderated mediation" framework to investigate how these contextual variables buffer or exacerbate the depletion of cognitive control. Identifying these moderators would allow instructional designers to develop adaptive systems that offer varying levels of support based on the specific cognitive demands of the learning activity [51].

The collection of data through self-reporting may be subject to respondent bias. Moreover, analyses conducted exclusively on Microsoft Teams cannot be directly generalized to other platforms. Future studies could entail the execution of comparative analyses across various platforms, such as Zoom, Moodle, and Blackboard. Qualitative studies could further explore the role of CCF in the process.

Ultimately, to extend the practical applicability of these findings beyond the Microsoft Teams environment, future research should prioritize the development and testing of "adaptive user interfaces" in diverse Learning Management Systems (e.g., Moodle, Canvas). Specifically, experimental studies should investigate design mechanisms that dynamically reduce information density—such as "focus modes" that hide peripheral menus—when high cognitive load is detected. Validating whether such adaptive interventions can preserve learners' cognitive control capacity across different educational technologies represents a critical frontier for next-generation instructional design [52].

In summary, the findings of the present study demonstrate that the CL experienced by students during the distance learning process has a negative effect on their PSU. However, the levels of CCF mitigate this negative effect and play a mediating role. These findings suggest that contemporary distance learning systems must be designed to be sensitive not only to technical adequacy but also to students' cognitive capacities. The reduction of CL and the facilitation of CCF skills have been demonstrated to significantly enhance the usability of online platforms and the learning experience. This result contributes to theoretical discussions in the field of educational technologies and guides system design and educational practices in practice. The research strongly emphasizes that in the digital age, focus should be placed not only on technical infrastructure but also on students' cognitive capacities and adaptability skills. It is of paramount importance to support students' CCF skills to ensure the effective and efficient use of distance learning platforms.

All the Declarations and Statements

Author Contributions Statement
Yener Yıldız – Conceptualization, Formal Analysis, Visualization, Statistical Analysis, Writing – Drafted the initial manuscript, Data Curation and Software Implementation.
Tayfun Yörük – Conceptualization, Methodology, Writing – Review and Editing, and Project Management, Validation Supervision

All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement
Data are available from the corresponding author upon reasonable request.

Ethical Declarations
The entire research process was conducted in full compliance with the ethical principles outlined in the Declaration of Helsinki [35]. The participation of students in the research was voluntary, personal data confidentiality was maintained, and approval was obtained from the Akdeniz University Social and Human Sciences Ethics Committee (Board Decision No. 247 dated April 22, 2025).

Declaration of Generative AI in Scholarly Writing
The authors declare that no generative artificial intelligence (AI) were used in the writing process of this manuscript.

Abbreviations
The following abbreviations are used in this manuscript:

NASA-TLX - National Aeronautics and Space Administration Task Load Index
CL - Cognitive Load
CLT - Cognitive Load Theory
PSU - Perceived System Usability
CCF - Cognitive Control and Flexibility
HCI - Human-Computer Interaction
SUS - System Usability Scale
CFI - Comparative Fit Index
TLI - Tucker-Lewis Index
RMSEA - Root Mean Square Error of Approximation
SRMR - Standardized Root Mean Square Residual
EEG - Electroencephalography

References

[1] O. Cetin, M. Cakiroglu, C. Bayılmış, and H. Ekiz, ‘The Importance of Education for Technological Development and the Role of Internet-Based Learning in Education’, Jun. 21, 2023, *arXiv*: arXiv:2306.12082. doi: 10.48550/arXiv.2306.12082.
[2] M. Tayebinik and M. Puteh, ‘Blended Learning or E-learning?’, Jun. 18, 2013, *arXiv*: arXiv:1306.4085. doi: 10.48550/arXiv.1306.4085.
[3] B. Shneiderman, C. Plaisant, and M. Cohen, *Designing the user interface: strategies for effective human-computer interaction*, 6th edn. USA: Pearson, 2016.
[4] J. Daniel, ‘QUALITY ASSURANCE AND ACCREDITATION IN DISTANCE EDUCATION AND E-LEARNING Models, Policies and Research FOREWORD’, *QUALITY ASSURANCE AND ACCREDITATION IN DISTANCE EDUCATION AND E-LEARNING: MODELS, POLICIES AND RESEARCH*. in Open and Flexible Learning Series. ROUTLEDGE, 11 NEW FETTER LANE, LONDON EC4P 4EE, ENGLAND, p. XIII–XVI, 2012.
[5] M. Özgöl, İ. Sarikaya, and M. Öztürk, ‘Örgün eğitimde uzaktan eğitim uygulamalarına ilişkin öğrenci ve öğretim elemanı değerlendirmeleri’, *Yükseköğretim ve Bilim Dergisi*, no. 2, pp. 294–304, 2017.

[6] M. Al Ghalayini, J. Antoun, and N. M. Moacdieh, 'Too much or too little? Investigating the usability of high and low data displays of the same electronic medical record', *Health Informatics J*, vol. 26, no. 1, pp. 88–103, Mar. 2020, doi: 10.1177/1460458218813725.
[7] J. Sweller, 'Cognitive load during problem solving: Effects on learning', *Cognitive science*, vol. 12, no. 2, pp. 257–285, 1988.
[8] J. Nielsen, *Usability engineering*. Morgan Kaufmann, 1994.
[9] J. F. Dumas and J. C. Redish, *A practical guide to usability testing*. Greenwood Publishing Group Inc., 1993. Accessed: Dec. 02, 2025. [Online]. Available: https://dl.acm.org/doi/abs/10.5555/573014
[10] D. Benyon, P. Turner, and S. Turner, *Designing interactive systems: People, activities, contexts, technologies*. Pearson Education, 2005.
[11] H. Kanis, 'Usage centred research for everyday product design', *Applied ergonomics*, vol. 29, no. 1, pp. 75–82, 1998.
[12] P. P. M. Hekkert and H. N. Schifferstein, 'Introducing product experience', in *Product experience*, Elsevier, 2008, pp. 1–8. Accessed: Dec. 02, 2025. [Online]. Available: https://research.tudelft.nl/en/publications/introducing-product-experience
[13] R. Kumar, D. Nagpal, V. Naik, and D. Chakraborty, 'Comparison of popular video conferencing apps using client-side measurements on different backhaul networks', in *Proceedings of the Twenty-Third International Symposium on Theory, Algorithmic Foundations, and Protocol Design for Mobile Networks and Mobile Computing*, Seoul Republic of Korea: ACM, Oct. 2022, pp. 241–246. doi: 10.1145/3492866.3557734.
[14] A. W. A. Wibowo, B. D. Rahmawati, and H. Mastrisiswadi, 'Video conferencing as a face-to-face online meeting app: User preference based on usability testing', *J. Sist. dan Manaj. Ind*, vol. 5, no. 2, pp. 98–104, 2021.
[15] D. A. Norman, *The psychology of everyday things.* Basic books, 1988.
[16] S. Krug, *Don't make me think!: a common sense approach to Web usability*. Pearson Education India, 2000.
[17] P. Chandler and J. Sweller, 'Cognitive Load Theory and the Format of Instruction', *Cognition and Instruction*, vol. 8, no. 4, pp. 293–332, Dec. 1991, doi: 10.1207/s1532690xci0804_2.
[18] F. Paas, J. E. Tuovinen, H. Tabbers, and P. W. Van Gerven, 'Cognitive load measurement as a means to advance cognitive load theory', in *Cognitive load theory*, Routledge, 2016, pp. 63–71. Accessed: Apr. 08, 2025. [Online]. Available: https://www.taylorfrancis.com/chapters/edit/10.4324/9780203764770-8/cognitive-load-measurement-means-advance-cognitive-load-theory-fred-paas-juhani-tuovinen-huib-tabbers-pascal-van-gerven
[19] J. Sweller, 'Cognitive load during problem solving: Effects on learning', *Cognitive science*, vol. 12, no. 2, pp. 257–285, 1988.
[20] A. S. Demirtaş, 'Stresli durumlarda bilişsel kontrol ve bilişsel esneklik: Bir ölçek uyarlama çalışması', *Psikoloji Çalışmaları*, vol. 39, no. 2, pp. 345–368, 2019.
[21] R. F. Baumeister, E. Bratslavsky, M. Muraven, and D. M. Tice, 'Ego depletion: Is the active self a limited resource?', in *Self-regulation and self-control*, Routledge, 2018, pp. 16–44. Accessed: Jan. 31, 2026. [Online]. Available: https://www.taylorfrancis.com/chapters/edit/10.4324/9781315175775-1/ego-depletion-roy-baumeister-ellen-bratslavsky-mark-muraven-dianne-tice
[22] M. J. Kane and R. W. Engle, 'The role of prefrontal cortex in working-memory capacity, executive attention, and general fluid intelligence: An individual-differences perspective', *Psychonomic Bulletin & Review*, vol. 9, no. 4, pp. 637–671, Dec. 2002, doi: 10.3758/BF03196323.
[23] R. L. Gabrys, N. Tabri, H. Anisman, and K. Matheson, 'Cognitive control and flexibility in the context of stress and depressive symptoms: The cognitive control and flexibility questionnaire', *Frontiers in psychology*, vol. 9, p. 2219, 2018.
[24] A. Diamond, 'Executive Functions', *Annu. Rev. Psychol.*, vol. 64, no. 1, pp. 135–168, Jan. 2013, doi: 10.1146/annurev-psych-113011-143750.
[25] A. I. Martins, A. G. Silva, J. Pais, V. T. Cruz, and N. P. Rocha, 'The impact of users' cognitive function on evaluator perceptions of usability', *Scientific Reports*, vol. 12, no. 1, p. 13753, 2022.
[26] A. F. Hayes, *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford publications, 2017.
[27] R. M. Baron and D. A. Kenny, 'The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations"', *Journal of personality and social psychology*, vol. 51, no. 6, p. 1173, 1986.
[28] K. J. Preacher and A. F. Hayes, 'Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models', *Behavior research methods*, vol. 40, no. 3, pp. 879–891, 2008.
[29] M. S. Fritz and D. P. MacKinnon, 'Required Sample Size to Detect the Mediated Effect', *Psychol Sci*, vol. 18, no. 3, pp. 233–239, Mar. 2007, doi: 10.1111/j.1467-9280.2007.01882.x.
[30] J. F. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, 'Multivariate data analysis'. New Jersey: Pearson Education Inc, 2010.
[31] T. A. Salthouse, 'Trajectories of normal cognitive aging.', *Psychology and aging*, vol. 34, no. 1, p. 17, 2019.
[32] B. J. Calder, L. W. Phillips, and A. M. Tybout, 'Designing research for application', *Journal of consumer research*, vol. 8, no. 2, pp. 197–207, 1981.
[33] S. G. Hart and L. E. Staveland, 'Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research', in *Advances in psychology*, vol. 52, Elsevier, 1988, pp. 139–183. Accessed: Apr. 08, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0166411508623869
[34] J. Brooke, 'SUS-A quick and dirty usability scale', *Usability evaluation in industry*, vol. 189, no. 194, pp. 4–7, 1996.
[35] W. M. Association, 'World Medical Association Declaration of Helsinki: ethical principles for medical research involving human subjects', *Jama*, vol. 310, no. 20, pp. 2191–2194, 2013.
[36] D. George and P. Mallery, *IBM SPSS statistics 29 step by step: A simple guide and reference*. Routledge, 2024. Accessed: Dec. 02, 2025. [Online]. Available: https://www.taylorfrancis.com/books/mono/10.4324/9781032622156/ibm-spss-statistics-29-step-step-darren-george-paul-mallery
[37] T. A. Brown, *Confirmatory factor analysis for applied research*. Guilford publications, 2015. Accessed: Dec. 02, 2025. [Online]. Available: https://books.google.com/books?hl=tr&lr=&id=tTL2BQAAQBAJ&oi=fnd&pg=PP1&dq=Confirmatory+factor+analysis+for+applied+research+&ots=amUvsOVM3E&sig=p3gaQwehQnUYNc3jU-YfYzZ2j9Q

[38] A. Miyake, N. P. Friedman, M. J. Emerson, A. H. Witzki, A. Howerter, and T. D. Wager, 'The unity and diversity of executive functions and their contributions to complex "frontal lobe" tasks: A latent variable analysis', *Cognitive psychology*, vol. 41, no. 1, pp. 49–100, 2000.
[39] K. J. Preacher and K. Kelley, 'Effect size measures for mediation models: quantitative strategies for communicating indirect effects.', *Psychological methods*, vol. 16, no. 2, p. 93, 2011.
[40] X. Zhao, J. G. Lynch Jr, and Q. Chen, 'Reconsidering Baron and Kenny: Myths and truths about mediation analysis', *Journal of consumer research*, vol. 37, no. 2, pp. 197–206, 2010.
[41] J. Cohen, *Statistical power analysis for the behavioral sciences*. routledge, 2013. Accessed: Jan. 31, 2026. [Online]. Available: https://www.taylorfrancis.com/books/mono/10.4324/9780203771587/statistical-power-analysis-behavioral-sciences-jacob-cohen
[42] R. B. Kline, 'The Mediation Myth', *Basic and Applied Social Psychology*, vol. 37, no. 4, pp. 202–213, Jul. 2015, doi: 10.1080/01973533.2015.1049349.
[43] M. E. Sobel, 'Asymptotic confidence intervals for indirect effects in structural equation models', *Sociological methodology*, vol. 13, pp. 290–312, 1982.
[44] J. J. Van Merrienboer and J. Sweller, 'Cognitive load theory and complex learning: Recent developments and future directions', *Educational psychology review*, vol. 17, no. 2, pp. 147–177, 2005.
[45] S. Hrastinski, 'Asynchronous and synchronous e-learning', *Educause quarterly*, vol. 31, no. 4, pp. 51–55, 2008.
[46] L. Cohen, L. Manion, and K. Morrison, *Research methods in education*. routledge, 2002. Accessed: Jan. 31, 2026. [Online]. Available: https://www.taylorfrancis.com/books/mono/10.4324/9780203224342/research-methods-education-keith-morrison-louis-cohen-lawrence-manion
[47] P. Sedgwick, 'Convenience sampling', *Bmj*, vol. 347, 2013, Accessed: Jan. 31, 2026. [Online]. Available: https://www.bmj.com/content/347/bmj.f6304.pdf+html
[48] [48]I. Etikan, S. A. Musa, and R. S. Alkassim, 'Comparison of convenience sampling and purposive sampling', *American journal of theoretical and applied statistics*, vol. 5, no. 1, pp. 1–4, 2016.
[49] T. Van Gog, F. Kirschner, L. Kester, and F. Paas, 'Timing and Frequency of Mental Effort Measurement: Evidence in Favour of Repeated Measures', *Applied Cognitive Psychology*, vol. 26, no. 6, pp. 833–839, Nov. 2012, doi: 10.1002/acp.2883.
[50] A. Korbach, R. Brünken, and B. Park, 'Measurement of cognitive load in multimedia learning: A comparison of different objective measures', *Instructional science*, vol. 45, no. 4, pp. 515–536, 2017.
[51] G. Orru and L. Longo, 'The Evolution of Cognitive Load Theory and the Measurement of Its Intrinsic, Extraneous and Germane Loads: A Review', in *Human Mental Workload: Models and Applications*, vol. 1012, L. Longo and M. C. Leva, Eds, in Communications in Computer and Information Science, vol. 1012. , Cham: Springer International Publishing, 2019, pp. 23–48. doi: 10.1007/978-3-030-14273-5_3.
[52] S. Oviatt, *The design of future educational interfaces*. Routledge, 2013. Accessed: Jan. 31, 2026. [Online]. Available: https://www.taylorfrancis.com/books/mono/10.4324/9780203366202/design-future-educational-interfaces-sharon-oviatt

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