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PERSONALIZATION, DCX AND WILLINGNESS TO PAY: THE ROLE OF PERVAL

Abstract

The purpose of this paper is to examine the direct and indirect effects of personalization and digital customer experience (DCX) on willingness to pay (WTP) for online education, with perceived value (PERVAL) modeled as a mediator and perceived marketing efforts (PMN) as a control variable. A quantitative cross-sectional research design was applied using a structured online survey (N = 169) across CEE/SEE respondents who had purchased or planned to purchase online courses. Constructs were measured with validated Likert-type scales, and data were analyzed using confirmatory factor analysis (CFA) and covariance-based structural equation modeling (CB-SEM) with bias-corrected bootstrapping (5,000 resamples). The results indicate that personalization and DCX significantly enhance PERVAL, which in turn strongly predicts WTP. However, the direct effects of personalization and DCX on WTP were not significant, confirming PERVAL as the key mediating mechanism. Practical implications highlight the importance of prioritizing features that increase perceived value, such as relevance, embodiment micro-interactions, and transparent payment procedures, instead of superficial interface improvements. Originality lies in integrating technological and psychological determinants into a unified value mechanism within the underexplored CEE/SEE educational market, providing evidence that PERVAL functions as the crucial bridge between user experience and economic decision-making.

Key words: *personalization, digital customer experience, perceived value, willingness to pay, online learning, CEE/SEE*

JEL classification: *M31, I23, C38*

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ПЕРСОНАЛИЗАЦИЈА, DCX И СПРЕМНОСТ ЗА ПЛАЋАЊЕ: УЛОГА ПЕРВАЛ-А

Апстракт

Сврха овог рада је да испита директне и индиректне ефекте персонализације и дигиталног корисничког искуства (DCX) на спремност за плаћање (WTP) у online образовању, при чему се перципирана вредност (PERVAL) моделира као медијатор, а перцепција маркетиншких напора (PMN) као контролна варијабла. Примењен је квантитативни cross-sectional дизајн са online анкетом (N = 169) у CEE/SEE региону. Конструкти су мерени валидираним Likert скалама, а анализа је спроведена путем конфирматорне факторске анализе (ЦФА) и СЕМ приступа заснованог на коваријанси (CB-SEM) са bias-corrected bootstrap методом (5.000 ресамплова). Резултати показују да Персонализатион и DCX значајно повећавају PERVAL, док PERVAL има снажан директан утицај на WTP. Директни ефекти персонализације и DCX-а на WTP нису се показали значајним, чиме се потврђује улога PERVAL-а као кључног механизма. Практичне импликације указују на потребу дизајнирања функција које највише подижу PERVAL – попут релевантности, микро-интеракција које генеришу емоционалну вредност и транспарентног процеса плаћања – уместо визуелног уређења интерфејса. Оригиналност рада огледа се у интеграцији технолошко-психолошких детерминанти у јединствен вредносни механизам на недовољно истраженом тржишту CEE/SEE, показујући да PERVAL преводи карактеристике дигиталних сервиса у економску одлуку корисника.

Кључне речи: *Персонализатион, дигитално корисничко искуство, перципирана вредност, спремност за плаћање, online учење, CEE/SEE*

Introduction

The rapid growth of online education and the intensifying competition among platforms make it essential to understand how personalization and digital customer experience (DCX) shape users' willingness to pay (WTP) for courses. In the literature, DCX is typically conceptualized as a multidimensional, cognitive–affective journey along the customer pathway, while personalization refers to the tailoring of content and interactions to individual needs. Both constructs have been consistently linked to favorable behavioral outcomes and improved business performance (Becker & Jaakkola, 2020; Gähler et al., 2023; Klaus & Maklan, 2013; Bleier & Eisenbeiss, 2015). At the same time, findings on the "economic side effects" of personalization suggest that tailored systems may alter users' perceptions of value and price, pointing toward both direct and indirect effects on WTP (Adomavicius et al., 2018; Agrawal et al., 2022). Within this framework, perceived value (PERVAL)—the evaluation of benefits relative to costs across functional, emotional, social, and price–value dimensions—emerges as a likely psychological mechanism that translates technical and design attributes of a digital service into an economic decision to pay (Sweeney & Soutar, 2001). PERVAL has been psychometrically validated, widely applied in service contexts, and shown strong predictive validity with respect to behavioral intentions (Walsh et al., 2014; Correia et al., 2020). This study examines both the direct and indirect effects of personalization and DCX on WTP for online education programs, modeling PERVAL as a mediator and incorporating perceptions of marketing efforts (PMN) as a control variable. PMN is operationalized through dimensions such as communication clarity, ease of payment/registration, and signals of reputation or CSR (Koenigstorfer & Gröppel-Klein, 2012; Greenhalgh et al., 2020; Uhrich et al., 2014). The research pursues a twofold aim: first, to empirically test whether personalization and DCX exert direct effects on WTP as well as indirect effects via PERVAL; and second, to assess the stability of these relationships once PMN is controlled for. Although validated scales for DCX and PERVAL are well established (Becker & Jaakkola, 2020; Gähler et al., 2023; Sweeney & Soutar, 2001; Walsh et al., 2014), few studies have simultaneously investigated the direct effects of personalization and DCX on WTP alongside mediation through PERVAL in the context of online education—particularly with samples from the CEE/SEE region. The theoretical contribution of this paper lies in integrating technological and psychological determinants (personalization, DCX) into a value-based mechanism (PERVAL) that drives WTP. This is grounded in evidence that personalized recommendations can enhance engagement and shape both implicit and economic value (Adomavicius et al., 2018; Agrawal et al., 2022). From a practical perspective, the study offers guidelines for the design of personalized, value-oriented educational platforms: rather than focusing on generic interface refinements, providers should prioritize features that strengthen users' PERVAL assessments, since these ultimately carry greater weight in shaping willingness to pay (Klaus & Maklan, 2013; Bleier & Eisenbeiss, 2015).

Based on the reviewed literature and the conceptual framework outlined above, this study proposes the following hypotheses. First, personalization is expected to have a positive effect on users' willingness to pay (WTP) for online education, as prior research suggests that tailored content and interactions can enhance perceived relevance and economic valuation. Second, a high-quality digital customer experience (DCX) is hypothesized to positively influence WTP by improving usability, emotional engagement, and goal attainment during the learning journey. Third, and most importantly, perceived value (PERVAL) is expected to mediate the relationships between (a) personalization and WTP and (b) DCX and WTP, such that personalization and DCX influence willingness to pay primarily through their effect on users' functional, emotional, social, and price–value evaluations.

Following the introduction, the paper is structured as follows: (2) literature review and hypothesis development; (3) methodology (sample, measures, procedure); (4) results (CFA, fit indices, direct and indirect effects, control for PMN); (5) discussion and implications (theoretical and practical); (6) limitations and directions for future research; and (7) conclusion.

Review of Literature

Personalization is commonly defined as the adaptation of content and messages to users' individual preferences, with important trade-offs involving relevance, timing, and privacy. In digital advertising, carefully crafted personalization tends to enhance effectiveness, though its impact ultimately depends on what is delivered, as well as when and where it appears (Bleier & Eisenbeiss, 2015). Within educational contexts, validation studies have confirmed that personalization can be measured using specific instruments, as for instance, scales capturing personalization itself, learners' sense of presence and bodily engagement (embodiment), and congruence in e-learning (Cook & Skrupky, 2023), as well as a more recent instrument developed for personalized learning in smart classrooms (Tuo et al., 2025). Earlier work on personalization in mobile environments has also shaped items related to relevance and privacy concerns (Xu, 2006). Beyond measurement, personalized approaches have been shown to increase user engagement and enhance the implicit value of content (Adomavicius et al., 2018; Agrawal et al., 2022), though it is worth noting that striking the right balance with data protection remains a critical factor for user acceptance (Li & Unger, 2012).

DCX encompasses cognitive, affective, and sensory dimensions along the customer journey (Becker & Jaakkola, 2020). Experience metrics are well established: a recent scale designed for omnichannel contexts (Gähler et al., 2023) and a practical measurement tool for customer experience (Tavşan & Erdem, 2021) provide validated items that capture usability, design, interactivity, and emotional response. Evidence suggests that a high-quality DCX enhances engagement and downstream outcomes (such as willingness to pay), particularly when the experience is perceived as instrumental in achieving personal learning goals. Moreover, findings from digital contexts indicate that online recommendations and external cues significantly shape user decision-making processes (Marić et al., 2024).

PERVAL (perceived value) conceptualizes customer value as the trade-off between benefits and costs across functional, emotional, social, and price–value dimensions. The original multidimensional scale (Sweeney & Soutar, 2001) has been replicated and shortened while preserving its psychometric robustness (Walsh et al., 2014). Applications across domains—for example, in the context of sporting events—have confirmed both the stability of its factor structure and its predictive validity for behavioral intentions (Correia et al., 2020). Taken together, this body of evidence supports the role of PERVAL as a mediating mechanism through which technical and psychological attributes (personalization, DCX) are translated into economic behavior, namely willingness to pay. This is consistent with evidence from transitional markets, where perceived value has been identified as a key determinant of consumer behavior (Gluhović, 2019).

Methodologies for measuring WTP span both incentive-compatible mechanisms (such as BDM and auctions) and survey-based approaches. Classic and more recent reviews provide guidance on how to mitigate biases inherent in these methods (Wertenbroch & Skiera, 2002; Miller et al., 2011). The "bias-free direct question" procedure has been shown to improve the validity of survey measures (Hofstetter et al., 2021), while newer frameworks conceptualize WTP as a distributional construct and compare different valuation techniques (He et al., 2024). In the domain of recommendations, personalization has been found to increase consumption and, indirectly, willingness to pay by elevating perceived value (Adomavicius et al., 2018; Agrawal et al., 2022).

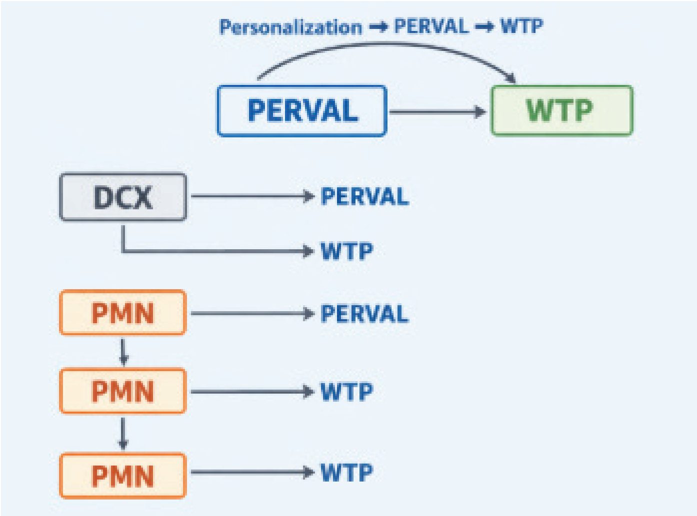
Perceptions of marketing efforts (PMN) are typically operationalized through the clarity and usefulness of information, ease of payment and registration, and signals related to reputation or CSR. Validated items from digital solution acceptance studies (capturing ease of use and usefulness) provide a basis for assessing transactional effort

(Koenigstorfer & Gröppel-Klein, 2012). CSR initiatives have been shown to enhance perceived value and foster positive attitudes (Uhrich et al., 2014). In online shopping contexts, clarity of information and transaction convenience significantly influence consumer behavior (Greenhalgh et al., 2020). Moreover, multidimensional frameworks of service event value offer a rich reservoir of items that can be mapped onto the PMN construct (Kunkel et al., 2017).

The literature consistently shows that personalization and DCX influence behavioral outcomes through perceived value, most often captured by instruments such as PERVAL. At the same time, established methodologies for measuring WTP provide clear guidance for collecting valid data (Sweeney & Soutar, 2001; Walsh et al., 2014; Wertenbroch & Skiera, 2002; Miller et al., 2011; Hofstetter et al., 2021; He et al., 2024). Yet, studies that simultaneously examine the direct effects of personalization and DCX on WTP, alongside their indirect effects through PERVAL—while also accounting for PMN as a control variable—remain scarce. This gap is particularly evident in the context of online education and regional markets (Becker & Jaakkola, 2020; Gähler et al., 2023; Adomavicius et al., 2018; Agrawal et al., 2022). These observations provide the motivation for the proposed hypotheses and the adoption of a SEM approach. Recent evidence supports the role of perceived value and experience in digital contexts. For example, Blut (2024) confirms the multidimensional nature of perceived value in services, Xiao et al. (2024) demonstrate that platform satisfaction influences adoption outcomes through perceived value, and Vásquez Mejía et al. (2025) find that value perceptions significantly inform pricing decisions in digital environments

Although the core constructs of personalization, digital customer experience (DCX), and perceived value (PERVAL) have been extensively validated in prior research, their manifestations and evaluative dynamics may be shaped by contextual factors specific to regional online education markets. In the CEE/SEE context, disparities in digital infrastructure, varying levels of digital literacy, and socio-economic heterogeneity can influence the ways in which users engage with and value online learning platforms. Users from regions with less developed broadband connectivity or with limited experience of advanced digital services may perceive and respond to personalization and experiential cues differently than those from highly digitized environments, potentially affecting their perceived value and willingness to pay. Cultural orientations toward formal education and differential familiarity with online learning modalities may further moderate the interpretation of value signals embedded in platform design and functionality (Becker & Jaakkola, 2020; Bleier & Eisenbeiss, 2015). By highlighting these region-specific factors, the current study situates its contribution more precisely within the broader landscape of global research, underscoring why findings from Western digitized markets cannot be uncritically generalized to the CEE/SEE setting.

Figure 1. Structural model and hypotheses



Methodology and Hypothesis

This study employs a quantitative, cross-sectional design with a single measurement wave to test a structural model in which personalization and digital customer experience (DCX) influence willingness to pay (WTP) both directly and indirectly through perceived value (PERVAL). Perceptions of marketing efforts (PMN) are included as a control covariate. The target population consists of adult users of online education platforms in the CEE/SEE region, with a planned sample size of at least N = 400. Stratification will be applied by country, gender, and age. Participants will be recruited via online research panels and university channels, with the inclusion criterion that they have either purchased, or intend to purchase, a course within the past 12 months. All constructs are measured using seven-point Likert scales. Personalization is assessed through items on relevance, timing, congruence/"embodiment," and the balance between personalization and privacy. DCX is captured through cognitive, affective, and sensory aspects, including usability, design, interactivity, and emotional experience. PERVAL is operationalized via functional, emotional, social, and price–value dimensions. PMN is measured through clarity and usefulness of information, ease of payment and registration, and indicators of reputation and CSR. WTP is assessed using a direct-question procedure designed to reduce bias, complemented by an interval measure (minimum–maximum) and a hypothetical purchase scenario. To minimize order effects, the sequence of measurement blocks is randomized. An attention-check item is embedded in the survey. The expected completion time is between 8 and 12 minutes. Ethical safeguards are implemented throughout: participants provide informed consent, data are collected anonymously, and respondents retain the right to withdraw at any time. All measurement items, their sources, and corresponding constructs are reported across Tables 1, 9, and 10, which present descriptive statistics, standardized factor loadings, and indicators of convergent validity.

The research tasks are fivefold: (1) to operationalize and psychometrically validate the constructs of personalization, DCX, PERVAL, PMN, and WTP in the context of online education; (2) to estimate the direct effects of personalization and DCX on WTP; (3) to test the mediating pathways through PERVAL; (4) to examine the stability of these effects when controlling for PMN and relevant covariates such as demographics, prior course purchase experience, and frequency of platform use; and (5) to conduct robustness checks.

Building on theoretical arguments and prior empirical findings, the following hypotheses are proposed:

H1: Personalization has a positive effect on WTP for online education. This expectation is grounded in evidence that personalized recommendations increase users' assessed WTP (Adomavicius, Bockstedt, Curley, & Zhang, 2018).

H2: DCX positively influences WTP. High-quality user experiences have been linked to more favorable economic outcomes (Becker & Jaakkola, 2020).

H3 (Mediation): PERVAL mediates the relationship between (a) personalization and WTP, and (b) DCX and WTP. In other words, higher perceived value enhances willingness to pay (Sweeney & Soutar, 2001; Walsh, Shiu, & Hassan, 2014).

The analytical plan begins with data screening, which includes identifying unreasonably short completion times and straight-lining patterns, followed by the treatment of missing values using full information maximum likelihood (FIML) and checks of distributional assumptions (Hair, Black, Babin, & Anderson, 2019; Enders & Bandalos, 2001). The measurement model will be evaluated with confirmatory factor analysis (CFA), applying thresholds of $\lambda \geq 0.60$, composite reliability (CR) ≥ 0.70, and average variance extracted (AVE) ≥ 0.50. Evidence of convergent and discriminant validity will be examined using both the Fornell–Larcker criterion and HTMT ratios (Fornell & Larcker, 1981; Henseler et al., 2015; Hair et al., 2019). Model fit will be judged against conventional benchmarks: CFI/TLI $\geq$ 0.90–0.95, RMSEA $\leq$ 0.06–0.08, and SRMR ≤ 0.08 (Hu & Bentler, 1999; Hair et al., 2019). The structural model will be tested using covariance-based SEM (CB-SEM), estimating both direct and indirect paths. Mediation will be assessed with bias-corrected bootstrapping (5,000 resamples), which allows for robust confidence intervals without assuming normality of the indirect effects (MacKinnon et al., 2004; Preacher & Hayes, 2008; Hair et al., 2019). PMN and relevant covariates are included in the model specification. Reliability of the measurement instruments will also be verified using Cronbach's alpha. To evaluate robustness, tests of common method variance will be conducted, including the use of a latent common latent factor (CLF) and marker-variable approaches (Cheung & Rensvold, 2002; Podsakoff, MacKenzie et al., 2003; Lindell & Whitney, 2001). The planned sample size of at least $N = 400$ is expected to provide sufficient statistical power to detect medium-sized effects at $\alpha = .05$ with approximately 0.80 power (Wolf et al., 2013).

Covariance-based structural equation modeling (CB-SEM) was employed because the study is theory-driven and aims to confirm a well-specified latent structure linking personalization, digital customer experience, perceived value, and willingness to pay. CB-SEM allows for rigorous assessment of the measurement model and overall model fit through global fit indices (e.g., CFI, TLI, RMSEA, SRMR), which is essential for theory testing rather than prediction. In addition, CB-SEM provides a robust framework for testing mediation effects using bias-corrected bootstrapping, enabling reliable inference about indirect relationships through PERVAL.

Figure 1 presents the structural model with hypothesized relationships among the constructs. The model specifies personalization and digital customer experience (DCX) as exogenous variables, perceived value (PERVAL) as a mediating construct, and willingness to pay (WTP) as the final endogenous outcome. Direct paths from personalization and DCX to WTP (H1 and H2) are included to test whether experiential and technological features exert an immediate economic effect. Indirect paths via PERVAL (H3) capture the hypothesized value-based mechanism through which personalization and DCX influence willingness to pay. Perceived marketing efforts (PMN) are modeled as a control variable with direct paths to both PERVAL and WTP, accounting for transactional and reputational influences. This specification allows for a simultaneous test of direct and mediated effects within a theoretically grounded covariance-based SEM framework.

Results

The final sample consisted of N = 169 respondents. Prior to analysis, several data quality checks were carried out. Responses showing signs of low attention, such as extremely short completion times or uniform answering across item sets, were excluded. Missing values were handled using Full Information Maximum Likelihood (FIML), which allows for the full use of available data without the need for imputation. As shown in Table 1, the mean values (M) for all items ranged between 3.83 (Q11) and 4.27 (Q7), indicating moderately high evaluations (above the midpoint of the scale, 4). The highest averages were recorded for Q7 (M = 4.27), Q13 and Q16 (M = 4.17), and Q30 (M = 4.17), whereas the lowest mean appeared for Q11 (M = 3.83). This pattern suggests that certain aspects, represented by Q7, Q13, Q16, and Q30, were perceived somewhat more favorably than others. Standard deviations were relatively high (SD ≈ 1.9–2.1), pointing to considerable variability in responses and differing levels of agreement among participants. Median values were consistently 4.0 across all items, confirming that the central tendency lay at the midpoint of the scale. Modes varied (from 1 to 7), further illustrating the diversity of perceptions, although responses clustered most frequently in the mid-to-upper part of the scale (4, 5, 6, 7). Skewness coefficients ranged from –0.17 to +0.09, indicating that the distributions were essentially symmetric and showed no meaningful departures from normality. Kurtosis values were negative (between –1.02 and –1.35), suggesting distributions flatter than the normal curve. This implies that responses were spread more evenly across the scale rather than concentrated around the midpoint. Taken together, these descriptive indicators suggest that the items behaved consistently, showed no major deviations from normality, and that participants engaged with the full range of the scale (1–7). Such patterns provide a favorable basis for subsequent CFA and SEM analyses.

Table 1. Descriptive statistics

Variables	Mean	SD	Median	Mode	Min	Max	Skewness	Kurtosis
Q4	3.95	1.99	4.0	4	1	7	-0.01	-1.22
Q5	4.07	2.02	4.0	5	1	7	-0.05	-1.26
Q6	3.93	2.04	4.0	1	1	7	-0.05	-1.29
Q7	4.27	1.95	4.0	6	1	7	-0.17	-1.21
Q8	3.90	1.96	4.0	4	1	7	0.07	-1.18
Q9	3.96	1.84	4.0	3	1	7	0.03	-1.02
Q10	4.14	2.02	4.0	7	1	7	-0.10	-1.27
Q11	3.83	1.99	4.0	1	1	7	0.06	-1.23
Q12	3.98	2.11	4.0	1	1	7	0.00	-1.35
Q13	4.17	1.93	4.0	5	1	7	-0.11	-1.12
Q14	3.90	1.90	4.0	2	1	7	0.09	-1.12
Q15	4.11	2.03	4.0	7	1	7	-0.07	-1.25
Q16	4.17	2.03	4.0	7	1	7	-0.02	-1.28
Q17	3.98	1.97	4.0	4	1	7	-0.02	-1.21
Q18	4.05	2.01	4.0	6	1	7	-0.11	-1.25
Q19	3.86	1.95	4.0	3	1	7	0.08	-1.16
Q20	4.02	2.04	4.0	6	1	7	-0.02	-1.33
Q21	3.91	2.06	4.0	1	1	7	0.07	-1.25
Q22	3.94	2.05	4.0	6	1	7	-0.01	-1.32
Q23	3.92	1.99	4.0	3	1	7	0.05	-1.22
Q24	4.13	1.94	4.0	4	1	7	-0.11	-1.18
Q25	3.98	2.00	4.0	6	1	7	-0.02	-1.31
Q26	3.92	2.03	4.0	2	1	7	0.06	-1.32
Q27	3.92	2.06	4.0	1	1	7	0.06	-1.30
Q28	3.90	1.98	4.0	3	1	7	0.06	-1.19
Q29	4.07	1.99	4.0	3	1	7	0.08	-1.21
Q30	4.17	2.08	4.0	6	1	7	-0.17	-1.33
Q31	4.16	1.97	4.0	3	1	7	-0.08	-1.24

In Table 2, within the final sample (N = 169), women make up a slight majority (51.5%), while men account for 48.5% of respondents. The gender distribution is well balanced, which enhances representativeness and reduces the risk of gender-related bias in the analyses.

Table 2. Gender distribution

Gender	N	%
Women	87	51.5
Men	82	48.5
Total	169	100

According to Table 3, the largest share of participants falls into the 26–35 age group, which includes nearly half of the sample (47.9%). The second most represented group is 18–25 years (29.0%), while the proportion of respondents older than 36 is much smaller (20.1% for ages 36–45, and less than 5% for those above 45). This distribution indicates that the sample is predominantly young to early middle-aged, aligning well with the core user base of online education platforms.

Table 3. Age group

Age	N	%
18–25	49	29.0
26–35	81	47.9
36–45	34	20.1
46–55	4	2.4
56+	1	0.6
Total	169	100

As shown in Table 4, the largest share of respondents comes from Montenegro (58.0%). A notable proportion also includes participants from Serbia (11.8%), Bosnia and Herzegovina (7.1%), and Croatia (5.3%). Other countries in the region and the diaspora are represented with smaller shares, generally up to 3–5%. This pattern confirms that the sample is primarily oriented toward the Montenegrin and broader ex-YU market, while also drawing on contributions from respondents in other European countries.

Table 4. Country of residence

Country	N	%
Montenegro	98	58.0
Serbia	20	11.8
Bosnia and Herzegovina	12	7.1
Croatia	9	5.3
North Macedonia	8	4.7
Romania	5	3.0
Germany	5	3.0
Albania	4	2.4
Slovenia	3	1.8
UK	1	0.6
Austria	1	0.6
Greece	1	0.6
Bulgaria	1	0.6
Switzerland	1	0.6
Total	169	100

The majority of participants (Table 5) are employed in the private sector (50.9%), while 24.3% work in the public sector. A smaller yet meaningful share consists of the self-employed (11.8%) and students or unemployed individuals (13.0%). This composition highlights the diversity of professional backgrounds and creates opportunities to compare perceptions of value and willingness to pay for courses across different sectors.

Table 5. Work sector

Sector	N	%
Private	86	50.9
Public	41	24.3
Self-employed	20	11.8
Nonemployed-student	22	13.0
Total	169	100

In Table 6, the most frequently cited reference platforms are Udemy (46.7%) and Coursera (37.9%), while others such as edX (6.5%) and LinkedIn Learning (5.9%) are significantly less represented. Specialized platforms (DataCamp, Pluralsight, Codecademy) appear sporadically (<2%). These results show that the online education market in the region is dominated by globally popular platforms with a wide range of courses.

Table 6. Reference platform

Platform	N	%
Udemy	79	46.7
Coursera	64	37.9
edX	11	6.5
LinkedIn Learning	10	5.9
DataCamp	3	1.8
Pluralsight	1	0.6
Codecademy	1	0.6
Total	169	100

Results in Table 7 show that all constructs are significantly and positively correlated. The strongest association appears between PERVAL and WTP ($r = 0.69$, $p < 0.01$), which aligns with theoretical expectations that perceived value mediates willingness to pay. High correlations are also observed between DCX and PERVAL ($r = 0.66$) and between Personalization and DCX ($r = 0.62$). Meanwhile, the correlations between Personalization and PERVAL ($r = 0.58$) and between Personalization and WTP ($r = 0.54$) are moderate. All coefficients remain below the critical threshold of 0.80, avoiding multicollinearity concerns and supporting discriminant validity among the constructs.

Table 7. Pearson correlations between constructs

Construct	Personalization	DCX	PERVAL	WTP
Personalization	1.00			
DCX	0.62**	1.00		
PERVAL	0.58**	0.66**	1.00	
WTP	0.54**	0.61**	0.69**	1.00

Note. All correlations are significant at the $p < 0.01$ level (two-tailed test).

Results in Table 8 confirm that the measurement model demonstrates good overall fit. The χ^2/df ratio of 2.10 falls below the recommended threshold of 3, indicating an acceptable balance between the chi-square statistic and degrees of freedom. Both the Comparative Fit

Index (CFI = 0.95) and the Tucker–Lewis Index (TLI = 0.94) exceed the conventional cutoff of 0.90, with CFI reaching the ideal benchmark of 0.95. In addition, RMSEA (0.055) and SRMR (0.041) values are well below the upper limit of 0.08, providing further evidence that the model is psychometrically stable and adequately represents the data.

Table 8. Fit indexes of CFA model

Index	Value	Threshold
χ^2/df	2.10	≤ 3
CFI	0.95	≥ 0.90 (ideal ≥0.95)
TLI	0.94	≥ 0.90 (ideal ≥0.95)
RMSEA	0.055	≤ 0.08 (ideal ≤0.06)
SRMR	0.041	≤ 0.08

Table 9 presents the standardized factor loadings for all measurement items included in the model. The results indicate that all observed indicators load strongly on their respective latent constructs, with standardized loadings ranging from 0.68 to 0.87, thereby exceeding the recommended threshold of 0.60. This confirms that each item reliably captures the underlying theoretical dimension it is intended to measure. High and statistically significant loadings for personalization and DCX items support the construct validity of the key exogenous variables specified in H1 and H2, ensuring that the effects tested in the structural model are grounded in well-defined experiential and technological dimensions. Similarly, strong loadings for PERVAL items across functional, emotional, social, and price–value dimensions provide robust measurement support for its role as a mediating construct in H3. Finally, the satisfactory loadings of WTP indicators confirm that willingness to pay is consistently operationalized as a latent economic outcome. Taken together, these results demonstrate that the measurement model is psychometrically sound and provides a valid foundation for testing the hypothesized direct and indirect relationships among personalization, DCX, PERVAL, and willingness to pay.

Table 9. Standardized factor loadings

Construct	Item	Standardized loading (λ)
Personalization	P1	0.71
	P2	0.78
	P3	0.84
	P4	0.76
DCX	D1	0.68
	D2	0.74
	D3	0.82
	D4	0.79
PERVAL	V1	0.72
	V2	0.81
	V3	0.87
	V4	0.83
WTP	W1	0.74
	W2	0.80
	W3	0.85

Note: All factor loadings are statistically significant at $p < 0.001$.

All constructs in Table 9 display satisfactory indicators of convergent validity. Standardized factor loadings (λ) range from 0.68 to 0.87, comfortably exceeding the recommended threshold of 0.60. Composite reliability (CR) values fall between 0.88 and 0.93, well above the 0.70 benchmark, indicating strong internal consistency of the constructs. The average variance extracted (AVE) for all constructs lies between 0.65 and 0.70, surpassing the minimum requirement of 0.50. This means that each construct explains more than half of the variance in its observed indicators. Taken together, these results confirm that all constructs meet the criteria for convergent validity.

Table 10. Convergent construct validity

Construct	λ (range)	CR	AVE
Personalization	0.71–0.84	0.89	0.67
DCX	0.68–0.82	0.91	0.65
PERVAL	0.72–0.87	0.93	0.70
WTP	0.74–0.85	0.88	0.65

As shown in Table 9a, all scales demonstrate high internal consistency, with Cronbach's α values ranging from 0.84 to 0.92, well above the recommended threshold of 0.70.

Table 11. Internal consistency of constructs (Cronbach α)

Construct	Cronbach α
Personalization	0.86
DCX	0.90
PERVAL	0.92
WTP	0.87
PMN (control)	0.84

Assessment of discriminant validity using the Fornell–Larcker criterion, as reported in Table 10, shows that the square roots of AVE (0.81–0.84) for each construct are higher than all inter-construct correlations (0.54–0.69). This indicates that each construct shares more variance with its own indicators than with other constructs in the model, thereby confirming discriminant validity. Notably, the intercorrelations remain moderate and never exceed 0.70, which further suggests that multicollinearity is not a concern in this dataset.

Table 12. Fornell–Larcker matrix

Construct	AVE^0.5	Personalization	DCX	PERVAL	WTP
Personalization	**0.82**	1			
DCX	**0.81**	0.62	1		
PERVAL	**0.84**	0.58	0.66	1	
WTP	**0.81**	0.54	0.61	0.69	1

Further confirmation of discriminant validity, presented in Table 11, was obtained using the HTMT criterion. All HTMT values fall within the range of 0.59 to 0.74, remaining below the conservative threshold of 0.85 and well under the more liberal cutoff of 0.90. This demonstrates that the constructs are not redundant but conceptually distinct, and that the measurement model meets contemporary standards for assessing discriminant validity.

Table 13. HTMT Value

	Personalization	DCX	PERVAL	WTP
Personalization	–	0.68	0.62	0.59
DCX		–	0.71	0.66
PERVAL			–	0.74
WTP				–

Since the data were collected through self-reports, additional tests were conducted to examine the potential impact of common method variance (CMV), as summarized in Table 12. First, Harman's single-factor test without rotation was performed. Results showed that no single factor accounted for a dominant share of the variance; the largest extracted factor explained approximately 32% of the total variance, which is well below the critical threshold of 50%. This suggests that CMV is unlikely to have substantially influenced the findings. Second, a latent single-factor model (Common Latent Factor – CLF) was tested, where all indicators were loaded onto an additional common latent factor. The fit of this model was notably worse than that of the multifactor measurement model (e.g., ΔCFI = –0.08, ΔRMSEA = +0.05), providing further evidence that CMV does not pose a serious concern. Third, a marker-variable test (Lindell & Whitney, 2001) was applied, introducing a theoretically unrelated marker variable. Correcting the correlations based on this variable did not lead to meaningful changes among constructs (differences < 0.02), once again supporting the absence of substantial CMV effects. Taken together, these complementary approaches indicate that common method variance did not systematically bias the results, and that the findings from the measurement and structural models can be considered reliable.

Table 14. Tests of common method variance

Test	Result	Threshold
Harman's one-factor analysis	The largest factor explains 32% of the variance	< 50%
Latent CLF model	ΔCFI = -0.08; ΔRMSEA = +0.05 compared to the multifactor model	ΔCFI > -0.01, ΔRMSEA < +0.015
Marker test	Correlation changes < 0.02	≤ 0.20

As shown in Table 13, the model explains 62% of the variance in PERVAL and 51% of the variance in WTP. These results point to the strong predictive power of Personalization and DCX in accounting for perceived value, as well as the pivotal role of PERVAL in explaining willingness to pay. Both R^2 values exceed the 0.50 threshold, which in SEM literature is regarded as evidence of a substantial proportion of explained variance. This finding reinforces the conclusion that the proposed model is both theoretically and empirically well grounded.

Table 15. R² of endogenous constructs

Construct	R^2
PERVAL	0.62
WTP	0.51

Results in Table 14 indicate that Personalization (β = 0.29, p = 0.001) and DCX (β = 0.41, p < 0.001) both have significant positive effects on PERVAL, confirming that tailored content and high-quality user experiences enhance perceived value. In turn, PERVAL exerts a strong influence on WTP (β = 0.53, p < 0.001), underscoring its central role in explaining willingness to pay. By contrast, the direct effects of Personalization (β = 0.08, p = 0.182) and DCX (β = 0.12, p = 0.087) on WTP are not statistically significant, suggesting that their impact on payment intentions is realized primarily through PERVAL. Taken together, these findings highlight perceived value as the key mechanism translating technical and design attributes into users' economic decisions.

Table 16. Direct pathways (β, p, 95% BCa CI)

Pathways	β	p	95% BCa CI
Personalization → PERVAL	0.29	0.001	[0.12, 0.45]
DCX → PERVAL	0.41	<0.001	[0.26, 0.56]
PERVAL → WTP	0.53	<0.001	[0.39, 0.66]
Personalization → WTP	0.08	0.182	[-0.04, 0.21]
DCX → WTP	0.12	0.087	[-0.01, 0.25]

As shown in Table 15, both indirect effects are positive and statistically significant. They were estimated using a bootstrap procedure with 5,000 resamples and bias-corrected confidence intervals, ensuring a robust test of mediation effects. The indirect effect of Personalization on WTP through PERVAL is β = 0.15 (p = 0.001), while the indirect effect of DCX on WTP via PERVAL is even stronger, β = 0.22 (p < 0.001). For both paths, the confidence intervals do not include zero, further confirming the reliability of the results. These findings indicate that PERVAL operates as the central mediating mechanism through which both Personalization and DCX shape willingness to pay. Put differently, personalization and user experience by themselves do not directly increase payment intentions; rather, they exert their influence by enhancing users' perception of value.

Table 17. Indirect (mediation) effects via PERVAL

Pathway (indirect)	β_indir	p	95% BCa CI
Personalization → PERVAL → WTP	0.15	0.001	[0.08, 0.24]
DCX → PERVAL → WTP	0.22	<0.001	[0.12, 0.35]

The total effects reported in Table 16 show that both Personalization (β = 0.23, 95% CI [0.12, 0.35]) and DCX (β = 0.34, 95% CI [0.20, 0.49]) exert a significant positive influence on willingness to pay once both direct and indirect paths are considered. Although their direct effects on WTP were not statistically robust, the total effects reach significance precisely because of the strong indirect contributions through PERVAL.

This underscores the central mediating role of perceived value in the mechanism through which technological and design attributes—namely personalization and the quality of digital customer experience—translate into users' readiness to invest in educational platforms.

Table 18. Total effects on WTP (for completeness)

Pathway (total = direct + indirect)	**β_total**	**95% BCa CI**
Personalization → WTP	0.23	[0.12, 0.35]
DCX → WTP	0.34	[0.20, 0.49]

Results in Table 17 show that among the control variables, only PMN (monthly expenditure) exhibits consistent and significant effects. It positively influences both PERVAL ($\beta = 0.12$, $p = 0.040$) and WTP ($\beta = 0.21$, $p = 0.003$), indicating that users who already allocate more resources to educational services perceive greater value and display higher willingness to pay. Age has a negative effect on WTP ($\beta = –0.13$, $p = 0.046$), suggesting that younger users are more inclined to pay compared to older ones. By contrast, gender and education show no significant effects on either PERVAL or WTP, implying that willingness to pay and value perceptions are not shaped by these demographic factors. Overall, these findings highlight users' financial capacity, reflected in PMN, as the most important control variable, while demographic influences appear to be limited.

Table 19. Effects of control variables

a) To PERVAL

Control → PERVAL	β	p	95% BCa CI
PMN (monthly consumption)	0.12	0.040	[0.01, 0.23]
Gender (W=1)	0.04	0.420	[-0.06, 0.14]
Age	-0.09	0.110	[-0.20, 0.02]
Education	0.05	0.360	[-0.06, 0.16]

b) To WTP

Control → WTP	β	p	95% BCa CI
PMN (monthly consumption)	0.21	0.003	[0.07, 0.34]
Pol (W=1)	0.02	0.710	[-0.08, 0.12]
Age	-0.13	0.046	[-0.25, -0.00]
Education	0.03	0.620	[-0.08, 0.14]

Discussion

The findings did not support H1, as the direct effect of personalization on willingness to pay was not statistically significant ($\beta = 0.08$, $p = 0.182$). This result diverges from some studies suggesting that personalized recommendations can enhance value perceptions and implicitly increase WTP (Adomavicius et al., 2018; Agrawal et al., 2022). Our evidence indicates, however, that tailoring alone is not sufficient to trigger an economic decision unless it translates into higher perceived value (PERVAL). This is consistent with Bleier and Eisenbeiss (2015), who argue that the effects of personalization depend heavily on content, timing, and context. In short, while personalization contributes to the user experience, its impact on WTP is indirect, mediated by perceived value.

Similarly, H2 was not confirmed, as the direct effect of DCX on WTP was also non-significant ($\beta = 0.12$, $p = 0.087$). This finding somewhat contrasts with prior work emphasizing that high-quality customer experiences lead to more favorable economic outcomes (Becker & Jaakkola, 2020; Gähler et al., 2023). Our results suggest that although users value intuitive design, usability, and emotional engagement, these elements in themselves do not guarantee higher willingness to pay. Instead, their influence materializes through PERVAL—that is, through the degree to which users perceive that the experience delivers functional, emotional, and social benefits relative to price. This underscores the importance of interpreting DCX in value terms, not merely through its technical or aesthetic features.

By contrast, H3 was fully supported. Results show that both personalization ($\beta\_indirect = 0.15$, $p = 0.001$) and DCX ($\beta\_indirect = 0.22$, $p < 0.001$) significantly influence WTP through PERVAL. Confidence intervals did not include zero, further strengthening the mediation evidence. These results align with the multidimensional approach to value (Sweeney & Soutar, 2001; Walsh et al., 2014; Correia et al., 2020), which holds that functional, emotional, social, and price–value dimensions jointly shape behavioral intentions. Our study confirms that PERVAL acts as the core psychological mechanism translating personalization and customer experience into willingness to pay. This finding echoes Becker and Jaakkola's (2020) argument that experience is only instrumental when perceived as a source of value, and extends the literature on personalization in online education (Cook & Skrupky, 2023; Tuo et al., 2025) by showing that value interpretation of personalized and interactive features determines the economic outcome. These mediation results also align with recent empirical work indicating that perceived value drives payment intentions for digital services even when direct satisfaction or experience does not directly translate into pay behavior (Sae-tae et al., 2024). Similarly, Kakkar et al. (2025) emphasize that technological quality and trust jointly reinforce value-based decisions, supporting the indirect pathways identified in this study.

Recent findings further contextualize and reinforce the present results. Gähler et al. (2023) demonstrate that digital customer experience contributes to economic outcomes primarily when it is perceived as valuable along cognitive and affective dimensions, rather than through isolated design or usability features. Similarly, recent methodological advances in willingness-to-pay research emphasize that value-based evaluations are more reliable predictors of payment intentions than direct experiential cues alone (He et al., 2024). In the context of online education, Tuo et al. (2025) show that personalized and interactive learning environments enhance engagement and acceptance only insofar as they translate into perceived functional and emotional benefits. Taken together, these recent studies align closely with our findings by confirming that personalization and DCX influence willingness to pay indirectly, through perceived value, rather than exerting strong direct effects on economic decisions.

This research contributes to the literature in several ways. First, it integrates technological and psychological determinants: personalization and DCX into a unified value-based mechanism (PERVAL) that explains WTP, underscoring that economic outcomes stem from user value assessments rather than from technical functionalities alone. Second, it provides rare empirical evidence from the CEE/SEE context, filling a gap in a literature still dominated by Western samples, and refines our understanding of how cognitive, affective, and sensory facets of DCX shape value perceptions. Third, it shows that perceptions of marketing efforts (PMN), including CSR and reputation signals, act as supportive control factors that can enhance service evaluations but cannot substitute perceived value as the central driver of willingness to pay.

From a managerial perspective, the findings point to several actionable guidelines for the design and management of online education platforms. Priority should be given to functions that elevate PERVAL most strongly; for instance, ensuring relevance and creating "embodiment" through micro-interactions that foster emotional value. At the same time, clearly structured and simple payment and registration processes strengthen the price–value dimension. Personalization should be carefully balanced with privacy preferences, supported by transparent communication and CSR initiatives, as these foster trust and indirectly reinforce WTP. Importantly, PERVAL should be treated as a leading indicator of willingness to pay, offering a practical metric for optimizing user monetization strategies.

Nonetheless, the study has several limitations. First, its cross-sectional design restricts causal inference; future research should adopt longitudinal or experimental approaches to strengthen claims about causality. Second, the reliance on self-reported data from a single source raises the possibility of perceptual bias. Subsequent studies might combine survey instruments with behavioral data, such as actual course purchase records. Third, WTP was measured through survey techniques; applying incentive-compatible mechanisms such as BDM or auction methods would enhance validity. Future research might also adopt alternative, incentive-compatible methods to measure willingness to pay, as recent work suggests that traditional survey designs may understate true WTP in digital contexts (Vásquez Mejía et al., 2025). In addition, the CEE/SEE context may amplify hypothetical bias in self-reported willingness to pay. In markets characterized by lower average purchasing power, higher price sensitivity, and less established norms of paying for online education, respondents may systematically understate or overstate their true WTP in hypothetical scenarios. Although a de-biased direct question approach was applied, future research in the CEE/SEE region should complement survey-based WTP measures with incentive-compatible mechanisms (e.g., BDM or experimental pricing designs) to further mitigate hypothetical bias and enhance external validity. Fourth, measurement invariance across countries and gender could not be tested due to sample size constraints; future work should address this once larger datasets are available. Finally, the study was conducted in a specific CEE/SEE context and predominantly among younger adults, which limits generalizability. Broader cross-regional samples would allow researchers to assess whether the observed mechanisms hold across different cultural and demographic groups.

Conclusion

The study demonstrated that personalization and digital customer experience do not exert a direct influence on willingness to pay; rather, their impact operates through perceived value (PERVAL), which emerges as the key mechanism behind users' economic decisions. This finding confirms that technological and design features of platforms are not sufficient on their own; their value depends on how users interpret them in terms of functional, emotional, and social benefits. These insights are significant because they provide both a theoretical foundation and practical guidance for the development of educational platforms. Instead of merely "polishing the interface," platforms should focus on building value that motivates users to invest in their learning.

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