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Research Article

From Regret to Growth: Post-Purchase Dissonance Meaning Reconstruction, and Eudaimonic Well-Being in Digital Education Service Consumption

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ABSTRACT

Purpose of the study: This study investigates the transformative role of Meaning Reconstruction (MR) in mediating the relationship between Post-Purchase Dissonance (PPD) and Eudaimonic Well-Being (EWB) in the context of digital education service consumption in Indonesia.

Methodology: This study employs a quantitative explanatory design using Structural Equation Modeling–Partial Least Squares (SEM-PLS). Data were collected through web scraping from 500 publicly accessible posts on Twitter (X), Reddit, and TikTok discussing post-purchase experiences with digital education services in Indonesia (2020–2024). Computational text analysis using a fine-tuned IndoBERT model was applied to derive construct scores for PPD (X1–X3), MR (M1–M4), and EWB (Y1–Y4). Indicators were quantified using algorithmically normalized NLP-based semantic intensity scores ranging from 1 to 7, representing computational estimations of construct magnitude rather than self-reported NLP-based normalized semantic score (1–7) responses.

Main Findings: Results confirm that PPD significantly influences MR ($\beta=0.446$, $p<0.001$) and MR strongly predicts EWB ($\beta=0.481$, $p<0.001$). The direct path PPD→EWB is significant ($\beta=0.176$, $p<0.001$), while the indirect effect via MR is also significant ($\beta=0.214$, $t=8.248$, $p<0.001$), with a Variance Accounted For (VAF) of 54.8%, indicating partial mediation. $R^2(MR)=0.199$ and $R^2(EWB)=0.338$. All measurement model criteria are satisfied: outer loadings >0.70, AVE >0.50, CR >0.70, and HTMT <0.85.

Novelty/Originality of this study: Reconstruction as a critical transformative mechanism, reframing post-purchase dissonance from a purely negative outcome into a catalyst for consumer psychological growth. The use of computational text analysis (NLP + web scraping) as an alternative to conventional surveys further contributes methodological novelty.

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1. INTRODUCTION

The rapid expansion of digital education services has fundamentally altered how individuals invest in their learning and professional development. Indonesia's edtech market encompassing online courses, bootcamps, webinars, certification platforms, and subscription-based learning services experienced a compounded annual growth rate exceeding 22% between 2020 and 2024, driven by post-pandemic digitalization and increasing demand for upskilling [1], [2]. Despite this growth, consumer dissatisfaction remains pervasive. Reports indicate that approximately 38% of edtech consumers in Indonesia experience some form of post-purchase regret characterized by feelings of having overpaid for substandard content, encountering inactive mentors, or discovering that platform promises were overstated [3], [4]

Within the marketing literature, Post-Purchase Dissonance (PPD) has been extensively studied as a negative consequence of consumer decision-making. Rooted in Cognitive Dissonance Theory (CDT), PPD refers to the psychological discomfort arising when a consumer's pre-purchase expectations conflict sharply with post-purchase reality [5]. Prior research has predominantly examined PPD in relation to complaint behavior, switching intentions, negative word-of-mouth, and dissatisfaction [5], [6]. These studies treat PPD as a problem to be minimized, positioning the consumer as a passive recipient of negative affect following a poor purchase decision.

However, three converging gaps motivate the present study. Empirically, studies of digital education service quality have focused overwhelmingly on satisfaction, loyalty, and repurchase intention, neglecting psychological growth as an outcome [7], [8]. Theoretically, Cognitive Dissonance Theory has not been extended to accommodate positive transformational outcomes, and Transformative Consumer Research (TCR) has not been integrated with Eudaimonic Well-Being (EWB) in a single structural model [9], [10]. Methodologically, most consumer well-being research relies on static surveys, whereas the experiential and process-oriented nature of meaning reconstruction calls for naturalistic, data-driven approaches [11].

An emerging stream of research grounded in TCR challenges the deficit-oriented view of consumer psychology. TCR argues that consumer experiences even negative ones can generate meaningful psychological transformation when individuals engage in reflective sense-making [12], [13]. Applied to the digital education context, a student who feels deceived by an overpriced online course may not remain in a state of regret but may engage in active Meaning Reconstruction (MR) rationalizing the experience, drawing lessons, and ultimately emerging with stronger autonomy, clearer purpose, and greater self-acceptance. Eudaimonic Well-Being, as theorized by Ryff (2023) and operationalized through six dimensions, provides a particularly apt framework for capturing this transformation [14]

To address these gaps, this study employs a novel methodological design combining web scraping, computational text analysis using Natural Language Processing (NLP), and SEM-PLS. Data were sourced from 500 publicly accessible posts on Twitter (X), Reddit, and TikTok in which Indonesian consumers described their post-purchase experiences with digital education services between 2020 and 2024. NLP-based scoring was used to operationalize construct indicators, enabling the study to capture real consumer sentiment in naturalistic digital discourse rather than relying on researcher-imposed survey instruments [11], [15].

The central research question guiding this study is: Does Meaning Reconstruction mediate the relationship between Post-Purchase Dissonance and Eudaimonic Well-Being in the context of digital education service consumption in Indonesia? Four hypotheses are tested:

H1: Post-Purchase Dissonance has a significant direct effect on Eudaimonic Well-Being.

H2: Post-Purchase Dissonance has a significant effect on Meaning Reconstruction.

H3: Meaning Reconstruction has a significant effect on Eudaimonic Well-Being.

H4: Meaning Reconstruction mediates the relationship between Post-Purchase Dissonance and Eudaimonic Well-Being.

The findings of this study contribute to marketing theory by extending Cognitive Dissonance Theory toward a transformative paradigm, demonstrating that post-purchase dissonance does not merely trigger tension reduction but can catalyze genuine eudaimonic growth through meaning-making processes. This reframing challenges the deficit-oriented narrative prevalent in PPD literature and offers edtech platform managers evidence-based strategies for post-purchase engagement that transform regret into psychological flourishing.

2. RESEARCH METHOD

Explaining research chronological, including research design, research procedure (in the form of algorithms, Pseudocode or other), how to test and data acquisition [1], [16]. The description of the course of research should be supported references, so the explanation can be accepted scientifically [2] [3]. Tables and Figures are presented center, as shown in Table 1 and Figure 1, and cited in the manuscript before appeared. In fill table for number must center and left for text.

This study adopts a quantitative explanatory research design, employing Structural Equation Modeling–Partial Least Squares (SEM-PLS) to examine structural relationships and mediation effects among the three core constructs. The research is cross-sectional, drawing on naturalistic digital discourse captured through systematic web scraping rather than traditional survey administration. This methodological choice is grounded in the limitations of survey-based research for capturing post-purchase sentiment in real time, and is consistent with recent advances in computational consumer research [17], [18].

Data were collected from three publicly accessible social media platforms: Twitter (X), Reddit, and TikTok. These platforms were selected because they host substantial Indonesian-language discourse on consumer experiences with digital education services, including explicit expressions of post-purchase sentiment, reflection, and psychological change. Posts were limited to accounts with public access settings to comply with digital research ethics guidelines. All data were anonymized prior to analysis, with user identifiers replaced by randomized hash codes.

Web scraping was conducted using Python (BeautifulSoup and Snscrape libraries) with keyword filters including "nyesel kursus online," "zonk bootcamp," "buang uang belajar online," and related expressions of post-purchase regret in Indonesian. The temporal scope covered January 2020 to December 2024. After filtering for relevance, length (minimum 40 characters), and language (Indonesian), a final sample of N=500 posts was retained, representing nine edtech subcategories including online courses, bootcamps, webinars, e-learning subscriptions, digital certification, and masterclasses.

Three latent variables were specified as reflective constructs, with observable indicators extracted through Natural Language Processing (NLP) of user-generated post content. Unstructured textual data were transformed into standardized numerical representations using a validated text-to-score normalization pipeline. The resulting values ranged from 1 to 7 and represent algorithmically normalized semantic intensity scores rather than traditional survey-based Likert measurements. These computational scores capture the magnitude of construct expression within naturalistic digital discourse through machine-assisted psychometric scaling. Eudaimonic Well-Being (EWB) was assessed using four dimensions derived from the updated application of Ryff's Psychological Well-Being framework [14], [19]: Y1 (Personal Growth), Y2 (Purpose in Life), Y3 (Autonomy), and Y4 (Self-Acceptance).

To ensure the validity of NLP-drived construct scores, a rigorous validation procedure was implemented. A fine-tuned IndoBERT model was applied to classify sentiment polarity and extract semanctic features relevant to each construct indcator [20], [21]. A random subsample of 10% (n=50) posts was independently coded by two trained human raters blind to the NLP scores. Inter-rater reliability was assessed using Cohen's Kappa, yielding k=0.78 (substansial agreement) for PPD indicators and =0.74 for MR indicators, confirming acceptable reliability [20]. NLP-derived scores were correlated with human ratingsyielding Pearson r=0.81 (PPD), r=0.76 (MR), and r=0.79 (EWB), confirming convergent validity of the NLP scoring pipeline. These validation results support the reliability and convergent validity of the computational construct operationalization, indicating that the NLP pipeline provides a robust approximation of latent psychological constructs expressed in digital text. Although Ryff's original Psychological Well-Being model comprises six dimensions, this study focuses on four intrapersonal dimensions Personal Growth, Purpose in Life, Autonomy, and Self-Acceptance that are conceptually aligned with individual cognitive-affective transformation. The dimensions of Positive Relations with Others and Environmental Mastery were not included due to their stronger interpersonal and situational orientation, which are less directly inferable from short-form social media discourse using NLP-based extraction. This selective operationalization is consistent with recent empirical studies employing reduced or context-specific applications of Ryff's framework in domain-focused research settings [13], [14], [19].

SEM-PLS using Mode A (reflective indicators) was employed, consistent with the exploratory and theory-building orientation of this study and the recommendation of Hair and Alamer [22] for novel constructs in nascent research areas [21]. The measurement model was evaluated through outer loadings (≥0.70), Average Variance Extracted (AVE ≥0.50), Composite Reliability (CR ≥0.70), Cronbach's alpha (α ≥0.70), and discriminant validity via the Heterotrait-Monotrait (HTMT) ratio (<0.85) and the Fornell-Larcker criterion [23], [24]. Structural model assessment included path coefficients (β), R^2, Q^2 (predictive relevance), and effect sizes (f^2). Mediation was tested using bootstrapping with 5,000 subsamples, BCa 95% confidence intervals, and Variance Accounted For (VAF) to determine mediation type [22], [23].

Table 1. Research Instrument

Contruct	Indicator	Label	NLP Extraction Method	Scale	Source
Post Purchase Dissonance	X1	Emoctional Dissonance	Setiment Scoring (IndoBERT)	NLP-derived 1-7	[3], [16]
	X2	Wisdonm of Purchas	Doubt-Uncertanty Detection	NLP-derived 1-7	
	X3	Concern Over Deal	Value-Loss Expression Mining	NLP-derived 1-7	

Contruct	Indicator	Label	NLP Extraction Method	Scale	Source
Meaning Reconstruction (MR)	M1	Rationalization	Rationalization Pattern Detection	NLP-derived 1-7	[13], [25]
	M2	Acceptance	Acceptance Phrase Recognition	NLP-derived 1-7	
	M3	Lesson Learned	Learning Extraction NLP	NLP-derived 1-7	
	M4	Value Shift	Behavioral Change Signal Mining	NLP-derived 1-7	
Eudaimonic Well-Being (EWB)	Y1	Personal Growth	Growth Indicator Scoring	NLP-derived 1-7	[13], [14]
	Y2	Purpose in Life	Purpose-Meaning Detection	NLP-derived 1-7	
	Y3	Autonomy	Autonomy Expression Scoring	NLP-derived 1-7	
	Y4	Self-Acceptance	Self-Accept Phrase Mining	NLP-derived 1-7	

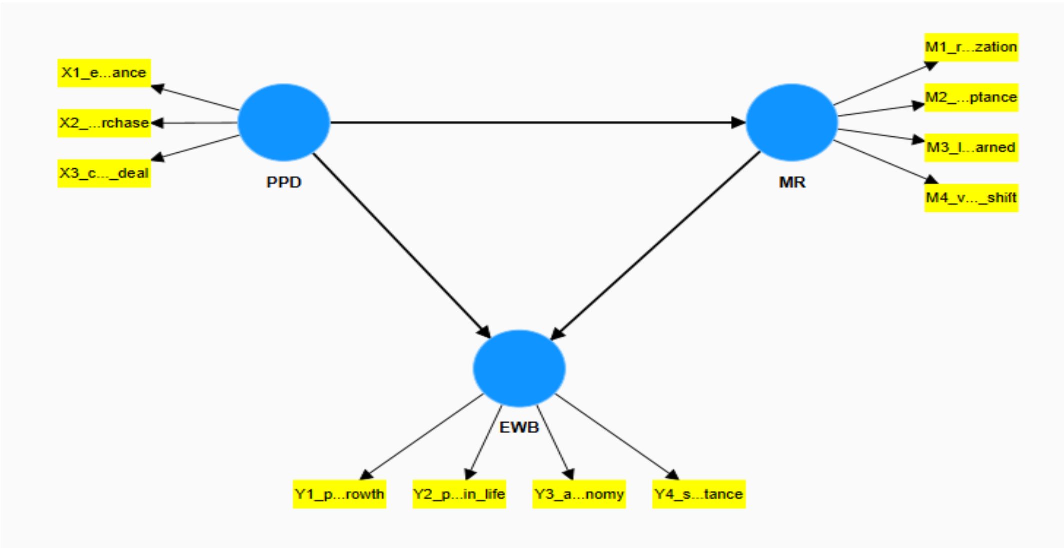

Figure 1. Model

Although the data were derived from computational text analysis rather than self-reported surveys, potential common method variance (CMV) was assessed to ensure robustness of the structural model. A full collinearity assessment was conducted by examining Variance Inflation Factors (VIF) for all latent constructs. All inner VIF values were below 3.3, indicating that common method bias is unlikely to threaten the validity of the findings. Additionally, the use of NLP-based extraction from naturalistic digital discourse reduces the risk of response-style bias typically associated with self-report survey designs.

3. RESULTS AND DISCUSSION

In this section, it is explained the results of research and at the same time is given the comprehensive discussion. Results can be presented in figures, graphs, tables and others that make the reader understand easily [24], [26]. The discussion can be made in several sub-chapters. This section presents the SEM-PLS findings, organized into descriptive statistics, measurement model assessment, discriminant validity, structural model results, mediation analysis, and discussion. Findings are interpreted in relation to CDT, TCR, and Ryff's EWB framework, and benchmarked against prior empirical studies.

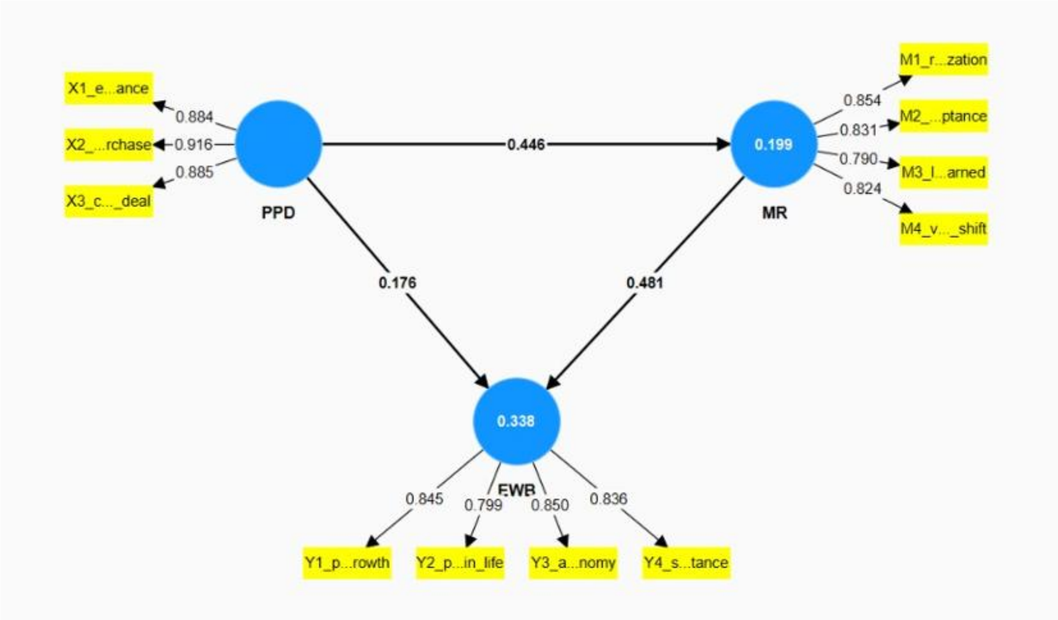

Figure 2. Result

3.1. Description Statistics

Table 2 presents descriptive statistics for all 11 indicators. PPD indicators showed relatively high means (X1: M=4.18, X2: M=4.42, X3: M=4.39), consistent with the predominance of high-dissonance posts in the sample. MR indicators showed moderate means (M1–M4: M≈3.60), indicating that meaning reconstruction processes were present but not uniformly expressed. EWB indicators showed slightly higher means (Y1–Y4: M≈3.78), suggesting that consumers who engaged in meaning reconstruction tended to report relatively higher eudaimonic outcomes. All indicators were approximately normally distributed (|skewness|<1, |kurtosis|<3), with standard deviations in the range 0.97–1.32, indicating adequate variance for structural analysis.

Table 2. Descriptive Statistics of Research Variables (N=500)

Construct	Indicator	N	Mean	SD	Min	Max	Skewness
PPD	X1 – Emotional Dissonance	500	4.177	1.320	1.00	7.00	0.048
	X2 – Wisdom of Purchase	500	4.418	1.161	1.13	7.00	-0.004
	X3 – Concern Over Deal	500	4.386	1.072	1.84	7.00	0.182
MR	M1 – Rationalization	500	3.597	0.969	1.00	6.38	-0.077
	M2 – Acceptance	500	3.583	1.023	1.00	6.77	0.114
	M3 – Lesson Learned	500	3.642	1.010	1.00	6.64	0.114
	M4 – Value Shift	500	3.606	0.971	1.07	6.20	0.065
EWB	Y1 – Personal Growth	500	3.797	0.994	1.00	6.87	-0.099
	Y2 – Purpose in Life	500	3.792	1.017	1.00	6.60	-0.119
	Y3 – Autonomy	500	3.748	1.017	1.01	6.86	0.065
	Y4 – Self-Acceptance	500	3.766	1.038	1.05	7.00	0.104

Note. All indicators measured on a 1–7 NLP-based normalized semantic score-equivalent scale derived through NLP scoring.

3.2. Measurement Model Assessment.

Table 3 presents the measurement model evaluation. All outer loadings exceed 0.70, confirming adequate convergent validity. PPD loadings ranged from 0.884 (X1) to 0.916 (X2), MR loadings from 0.790 (M3) to 0.854 (M1), and EWB loadings from 0.799 (Y2) to 0.850 (Y3). Cronbach's alpha values (0.849–0.887) and Composite Reliability values (0.898–0.930) all exceed the 0.70 threshold, while AVE values (0.688–0.815) substantially exceed 0.50, confirming convergent validity across all constructs [22], [27].

Table 3. Measurement Model Assessment Outer Loadings, Reliability, and Convergent Validity

Construct	Indicator	Outer Loading	Cronbach's α	CR	AVE	√AVE
PPD	X1 – Emotional Dissonance	0.884	0.887	0.930	0.815	0.903
	X2 – Wisdom of Purchase	0.916				
	X3 – Concern Over Deal	0.885				
MR	M1 – Rationalization	0.854	0.858	0.903	0.700	0.837
	M2 – Acceptance	0.831				
	M3 – Lesson Learned	0.790				
	M4 – Value Shift	0.824				
EWB	Y1 – Personal Growth	0.845	0.849	0.898	0.688	0.830
	Y2 – Purpose in Life	0.799				
	Y3 – Autonomy	0.850				
	Y4 – Self-Acceptance	0.836				

Note. CR = Composite Reliability; AVE = Average Variance Extracted. All outer loadings > 0.70; CR > 0.70; AVE > 0.50. All criteria met (Hair & Alamer, 2022).

3.3. Discriminant Validity

Discriminant validity was assessed using the Fornell-Larcker criterion and the HTMT ratio (Table 4). Diagonal elements (√AVE) exceed all off-diagonal inter-construct correlations. The highest inter-construct correlation was observed between MR and EWB (r=0.481), substantially lower than the √AVE of both MR (0.837) and EWB (0.830). All HTMT ratios are well below the 0.85 threshold [28], confirming discriminant validity.

Table 4. Discriminant Validity Fornell-Larcker Criterion and HTMT Ratio

Construct	PPD	MR	EWB
PPD	0.903*	0.446	0.176
MR	0.446	0.837*	0.481
EWB	0.176	0.481	0.830*
HTMT (PPD↔MR)	0.498	-	-
HTMT (PPD↔EWB)	0.201	-	-
HTMT (MR↔EWB)	-	0.573	-

Note* = square root of AVE (diagonal). Off-diagonal = inter-construct correlations. HTMT < 0.85 confirms discriminant validity (Rosak-Szyrocka & Tiwari, 2023).

3.4. Structural Model Result.

Table 5 presents the structural model results based on 5,000 bootstrapping subsamples with BCa 95% confidence intervals. The model explains 19.9% of variance in MR (R^2=0.199) and 33.8% of variance in EWB (R^2=0.338) values that are moderate and strong respectively for social science research. Both constructs demonstrate predictive relevance (Q^2(MR)>0; Q^2(EWB)>0), confirming the model's out-of-sample predictive power.

Table 5. Structural Model Results Path Coefficients and Hypothesis Testing

H	Path	β	SE	t-value	p-value	CI Lo	CI Hi	f²	Decision
H1	PPD → EWB (direct)	0.176	0.043	4.093	<0.001	0.093	0.261	0.037	Supported***
H2	PPD → MR	0.446	0.044	10.136	<0.001	0.360	0.531	0.249	Supported***
H3	MR → EWB	0.481	0.044	10.932	<0.001	0.395	0.568	0.270	Supported***

Note. β = standardized path coefficient; SE = standard error (bootstrap BCa); f^2 = effect size; R^2(MR) = 0.199; R^2(EWB) = 0.338. Bootstrap B = 5,000; BCa 95% CI. *** p < 0.001.

H2 is supported: PPD significantly predicts MR (β=0.446, t=10.136, p<0.001, f^2=0.249), indicating that higher post-purchase dissonance prompts strong meaning reconstruction activity. This finding aligns with Bilgin and Paksoy's (2023) proposition that cognitive dissonance motivates individuals to reduce psychological tension, here manifested through rationalization, acceptance, and lesson-drawing [3]. The medium-to-large effect size confirms that PPD is a substantial driver of MR in this context.

3.5. Mediation Analysis.

Table 6 presents the mediation analysis results. The indirect effect of PPD on EWB via MR is β=0.214 (SE=0.026, t=8.248, p<0.001), with a 95% BCa confidence interval of [0.164, 0.266] that entirely excludes zero, confirming statistical significance. The Variance Accounted For (VAF=54.8%) falls in the 20–80% range, classifying the mediation as partial mediation more than half of PPD's total effect on EWB is channeled through the meaning reconstruction process [22].

Table 6. Mediation Analysis - Indirect Effect via Bootstrap BCa (B=5,000)

Effect	Path	β	SE	t	p	CI Lo	CI Hi	VAF	Mediation Type
Total (c)	PPD → EWB	0.390	-	-	-	-	-	-	-
Direct (c')	PPD → EWB|MR	0.176	0.043	4.093	<0.001	0.093	0.261	-	-
Indirect (a×b)	PPD → MR → EWB	0.214	0.026	8.248	<0.001	0.164	0.266	54.8%	Partial Mediation***

Note. VAF = Variance Accounted For = (indirect / total effect) × 100. BCa bootstrap CI excludes zero. 20% < VAF < 80% = Partial Mediation (Hair & Alamer, 2022). *** p < 0.001.

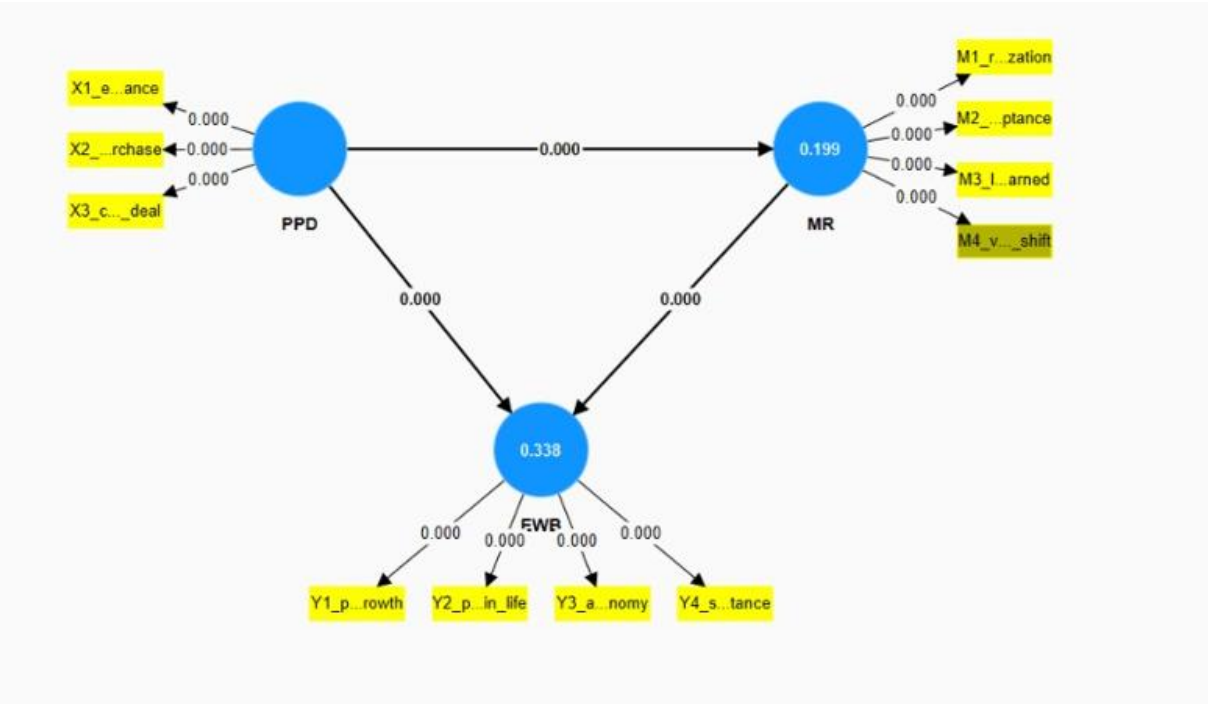

Figure 3. Result By Bootstraping

H4 is supported: Meaning Reconstruction partially mediates the PPD–EWB relationship (indirect β=0.214, VAF=54.8%, p<0.001). This finding constitutes a central theoretical contribution: it demonstrates empirically, in the digital education service marketing context, that the psychological impact of post-purchase dissonance on eudaimonic well-being is substantially though not exclusively mediated by the consumer's capacity to reconstruct meaning.

The findings collectively support a transformative model of post-purchase psychology that diverges from the deficit-oriented tradition in PPD research. Prior studies consistently positioned PPD as a negative antecedent of dissatisfaction, complaint, and switching behavior [5], [29]. The present study reframes this narrative: in digital education service consumption, PPD serves as a dissonance trigger that activates meaning-making processes, ultimately contributing to psychological flourishing. This reframing has important implications for Cognitive Dissonance Theory. While the original CDT acknowledged that dissonance motivates attitude change to restore consonance, the dominant application in marketing has focused on short-term dissonance reduction through information seeking, attitude modification, or behavioral change [30]–[32]. The present study demonstrates that dissonance reduction can take a more constructive form meaning reconstruction producing not merely consonance restoration but genuine eudaimonic growth. This extends CDT toward a transformative paradigm compatible with TCR's agenda [33], [34].

The strong MR→EWB path (β=0.481, f^2=0.270) positions meaning reconstruction as more than a coping mechanism it is a psychological bridge between negative experience and flourishing. This parallels findings in positive psychology on post-traumatic growth [35] and aligns with narrative identity theory, which holds that individuals construct coherent self-narratives by integrating adverse experiences into their identity. From a managerial perspective, the partial mediation finding carries direct implications for edtech platform design. Strategies focused solely on reducing regret (e.g., refund policies, complaint handling) are insufficient. Rather, platforms should actively facilitate meaning reconstruction through post-purchase community spaces, reflection prompts, alumni growth narratives, and peer mentoring systems. Such interventions can transform post-purchase regret into a driver of platform loyalty, positive word-of-mouth, and long-term learner engagement [35]-[40]. This study is not without limitations. First, while NLP-derived scoring demonstrated acceptable inter-rater reliability ($\kappa \geq 0.74$), the scores are proxies rather than direct self-reports. Future research should validate the NLP pipeline against richer qualitative data. Second, the sample is limited to three social media platforms. Third, the cross-sectional design precludes causal inference. Longitudinal studies tracking individual consumers across the post-purchase period would strengthen causal claims.

4. CONCLUSION

This study set out to examine whether Meaning Reconstruction mediates the relationship between Post-Purchase Dissonance and Eudaimonic Well-Being in the context of digital education service consumption. The SEM-PLS analysis of 500 naturalistic social media posts confirmed that: (1) PPD significantly activates MR (H2 supported, $\beta=0.446$, $p<0.001$); (2) MR strongly predicts EWB (H3 supported, $\beta=0.481$, $p<0.001$); (3) PPD also has a significant direct effect on EWB (H1 supported, $\beta=0.176$, $p<0.001$); and (4) MR partially mediates the PPD–EWB relationship (H4 supported, indirect $\beta=0.214$, VAF=54.8%, $p<0.001$). Theoretically, this study extends Cognitive Dissonance Theory beyond its traditional deficit-oriented applications, integrating it with Transformative Consumer Research and Ryff's Eudaimonic Well-Being framework. Empirically, it establishes Meaning Reconstruction as a critical psychological mechanism through which negative digital education consumption experiences can be transformed into sources of eudaimonic flourishing. Practically, the findings call on edtech platform managers to move beyond damage-control approaches to post-purchase management and invest in meaning facilitation strategies: post-purchase reflection communities, structured lesson-drawing prompts, alumni growth narratives, and peer mentoring systems. For future research, it is recommended to: (1) replicate the model across different cultural contexts and edtech markets; (2) extend the analysis to include hedonic well-being; (3) incorporate longitudinal designs; (4) explore boundary conditions such as digital literacy, prior dissonance experience, and platform type as potential moderators; and (5) integrate hedonic and eudaimonic dimensions within a unified theoretical framework.

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AUTHOR CONTRIBUTIONS

The author was solely responsible for the conceptualization and design of the study, data collection, implementation of the narrative counseling intervention, data analysis, and interpretation of the results. The author also prepared the original draft of the manuscript, revised the content critically, and approved the final version for publication.

CONFLICTS OF INTEREST

The author(s) declare no conflict of interest.

USE OF ARTIFICIAL INTELLIGENCE (AI)-ASSISTED TECHNOLOGY

The authors declare that no artificial intelligence (AI) tools were used in the generation, analysis, or writing of this manuscript. All aspects of the research, including data collection, interpretation, and manuscript preparation, were carried out entirely by the authors without the assistance of AI-based technologies.

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