Analysis of Psychological Factors Affecting Customer Lifetime Value on SaaS Platforms

Apeksha Siddannavar[1], Prof. Shoaib Ahamed Khan[2], Prof. Pooja Ravindra Takalkar[3]

[1]Student, Business Analytics, RV Institute of Management
[2,3]Assistant Professor, Marketing, RV Institute of Management

Abstract
This study investigates the psychological factors that influence Customer Lifetime Value (CLV) in Software-as-a-Service (SaaS) platforms, shifting focus from purely transactional metrics to human-centred determinants of long-term customer engagement. Drawing on theories from psychology and marketing, the paper explores how trust, satisfaction, emotional branding, perceived benefits, and awareness impact CLV. The proposed conceptual framework highlights the direct and indirect roles of self-efficacy and prior knowledge in shaping customer awareness and perceived benefits, both of which contribute to increase CLV. Key psychological drivers such as onboarding satisfaction, emotional loyalty, and perceived switching costs are analysed alongside strategies like gamified engagement and personalized loyalty programs. The paper identifies gaps in traditional CLV modelling, particularly the lack of psychological segmentation and longitudinal insights. It also emphasizes the importance of trust and data transparency in building emotional bonds that sustain customer loyalty. The findings suggest that integrating psychological variables into CLV models enables SaaS companies to enhance customer experience, reduce churn, and improve profitability. This research offers a comprehensive framework for SaaS firms to develop emotionally resonant, personalized retention strategies rooted in customer psychology.

Keywords: Customer Lifetime Value, Psychological Factors, SaaS Platforms, Customer Retention.

Introduction

Over the past decade, a growing body of research has examined the drivers of Customer Lifetime Value (CLV) in subscription-based businesses, with a particular focus on Software-as-a-Service (SaaS) platforms. Early foundational studies emphasized transactional metrics such as usage frequency, contract length, and average revenue per user as primary predictors of CLV (Gupta & Lehmann, 2003). More recent investigations have begun to integrate behavioral economics and psychological constructs, exploring how customer satisfaction, perceived benefits, and emotional loyalty contribute to retention and upsell potential (Kumar & Reinartz, 2016). Scholars have applied theoretical frameworks such as the Technology Acceptance Model (TAM) and relationship marketing to demonstrate that trust in the vendor, perceived ease of use, and alignment with customer self-concept are significant antecedents to ongoing subscription commitment (Gefen, Karahanna, & Straub, 2003; van Doorn et al., 2010). These interdisciplinary approaches collectively underscore that psychological factors can be as determinative as traditional usage metrics in forecasting long-term revenue streams for SaaS firms.

Despite these advances, extant literature often treats psychological drivers in isolation or focuses on discrete elements such as satisfaction or trust without examining their interrelationships or cumulative impact on CLV in a unified, dynamic framework. Moreover, most empirical work has relied on cross-sectional survey data, limiting insights into how psychological factors evolve over the customer journey and affect churn risk at different stages. There is also a notable lack of longitudinal and multi-method studies that combine behavioral analytics with psychometric assessments to capture temporal shifts in customer attitudes. Furthermore, research addressing individual differences such as customer's propensity for risk, need for cognition, or value-based decision-making styles and how these traits moderate the influence of service perceptions on renewal intentions and upsell behaviours remains scarce.

SaaS providers today face intensifying competition and rising acquisition costs, with average customer acquisition costs often exceeding hundreds of dollars per user. Under these conditions, retention and expansion of existing accounts become paramount for sustainable growth. However, without a nuanced understanding of the psychological mechanisms that underpin customer loyalty and advocacy, marketing and customer success teams often resort to reactive churn mitigation tactics such as blanket discounts or generic outreach that fail to address root causes of disengagement. This misalignment not only undermines revenue potential but also risks eroding brand equity and customer trust. The core problem, therefore, is the absence of actionable insights into which psychological levers be they cognitive, emotional, or social influence, different segments of the user base at specific lifecycle junctures, and how these levers can be operationalized to maximize CLV.

An in-depth analysis of psychological factors affecting CLV on SaaS platforms stands to benefit multiple stakeholders across the organization. For marketing leaders, it offers a data-driven roadmap to personalize acquisition and retention campaigns by aligning messaging with customer's intrinsic motivations and behavioral profiles. Customer success managers can leverage insights into individual decision-making styles to tailor onboarding experiences, anticipate friction points, and proactively nurture high-value accounts, thereby reducing churn. From a product management perspective, understanding the emotional and cognitive drivers of perceived benefits can guide feature prioritization, user-experience enhancements, and roadmap decisions that foster deeper engagement. Additionally, finance teams and executives gain a more robust forecasting tool that integrates qualitative customer psychology with quantitative financial metrics, enabling more accurate revenue projections, budget allocations, and strategic planning. Ultimately, bridging the gap between psychological theory and subscription economics equips SaaS organizations with the predictive and prescriptive capabilities necessary to cultivate enduring, high-value customer relationships.

Research on Customer Lifetime Value (CLV) in SaaS has progressively acknowledged that psychological constructs such as satisfaction, trust, and perceived benefits are not merely peripheral but central to predicting retention and revenue streams (Gupta & Lehmann, 2003; Kumar & Reinartz, 2016). This paradigm shift underscores the necessity of treating customer psychology as an integral component of CLV models rather than an afterthought (Gefen, Karahanna, & Straub, 2003).

With customer acquisition costs soaring often exceeding sustainable thresholds SaaS providers can ill afford reactive, one-size-fits-all retention tactics that erode margins and dilute brand loyalty (Gupta & Lehmann, 2003). Without proactive understanding of the psychological triggers of churn, organizations remain blind to root causes of disengagement (Gefen et al., 2003). Thus, integrating psychological profiling into customer success is imperative.

Despite this recognition, existing frameworks seldom integrate cognitive, emotional, and social drivers into a unified, dynamic CLV algorithm (van Doorn et al., 2010). Moreover, the dearth of longitudinal, multi-method studies means firms lack insight into how psychological factors evolve across the subscription lifecycle (Kumar & Reinartz, 2016). Addressing this gap is essential to operationalize psychographic metrics in real-time analytics.

In context of the above, the study intends to meet the following objectives:

1. To assess the role of awareness and prior knowledge in fostering self-efficacy impacting customer lifetime value.
2. To examine the impact of self-efficacy on the level of perceived benefits of a customer on SaaS platforms.
3. To explain the significance of perceived benefits and self-efficacy on overall customer lifetime value.

Literature Review

Customer Lifetime Value (CLV) has become a fundamental metric in marketing, playing a crucial role in shaping strategies for customer acquisition, retention, and resource allocation. Various studies have explored CLV modelling methodologies, highlighting their significance in long-term business profitability. By accurately estimating CLV, businesses can make informed decisions regarding customer segmentation, personalized marketing, and long-term revenue optimization. Understanding CLV is especially critical in subscription-based models, such as Software-as-a-Service (SaaS), where continuous engagement and customer retention drive profitability.

Gupta et al. (2006) underscore the importance of CLV in evaluating long-term customer profitability over short-term sales. Their study reviews different CLV estimation techniques, including probability-based, econometric, and machine-learning models, illustrating the impact of marketing efforts on customer retention and expansion. However, challenges such as cost allocation and data integration persist, requiring future research to incorporate network effects and macroeconomic influences. Similarly, Berger and Nasr (1998) focus on CLV applications in direct marketing, introducing systematic mathematical models that consider customer retention probabilities. Their research highlights the importance of balancing marketing expenditures between customer acquisition and retention to maximize profitability.

To improve predictive accuracy, Borle, Singh, and Jain (2008) introduced a hierarchical Bayesian approach to CLV measurement, which captures individual-level variations. Their findings indicate that while longer interpurchase times correlate with higher spending, they also increase the risk of customer defection. Chang, Chang, and Li (2012) further refine CLV models by categorizing them into scoring, probability, and econometric frameworks, advocating for the integration of CLV with financial metrics to enhance marketing accountability.

In advocating a shift from product-centric to customer-centric marketing, Kumar (2007) emphasizes the role of CLV in guiding resource allocation and segmentation. He identifies key CLV drivers, including customer retention, purchase frequency, and cross-selling opportunities, while addressing challenges such as data collection and model refinement. Malthouse and Blattberg (2005) analyse the predictive accuracy of CLV models and reveal significant risks of misclassification. They propose adaptive marketing strategies to mitigate segmentation errors, further reinforcing the need for dynamic and responsive marketing approaches.

Expanding on CLV's strategic applications, Venkatesan and Kumar (2004) develop a dynamic CLV framework aimed at optimizing customer selection and marketing resource allocation. Their research demonstrates that CLV driven strategies lead to higher long-term profitability compared to traditional customer valuation metrics such as Recency Frequency Monetary (RFM) analysis. Additionally, Stahl, Matzler, and Hinterhuber (2003) establish a direct link between CLV and shareholder value, emphasizing that effective CLV management enhances cash flow stability and overall firm valuation.

In terms of segmentation and predictive analytics, Kim et al. (2006) introduce a CLV-based customer segmentation model that incorporates current value, potential value, and customer loyalty. Rosset et al. (2003) propose a segment-based CLV estimation framework that proves effective for churn analysis and retention campaign management. Expanding on churn prediction, Glady, Baesens, and Croux (2009) redefine churn modelling by integrating CLV as a central metric. Their research highlights the critical role of CLV in prioritizing retention efforts, particularly for high-value customers, demonstrating how businesses can leverage CLV insights to enhance customer relationship management.

Parallel to advancements in CLV modelling, Software-as-a-Service (SaaS) has emerged as a crucial component of cloud computing, offering scalable, cost-effective, and flexible software solutions. Researchers have examined various aspects of SaaS, including its architecture, benefits, adoption determinants, governance structures, and security challenges. As businesses increasingly transition to cloud-based software models, understanding the relationship between CLV and SaaS adoption becomes essential for maximizing customer lifetime profitability in a subscription-based economy.

Software-as-a-Service (SaaS) has emerged as a critical component of cloud computing, offering organizations a cost-effective and scalable solution for software deployment. Unlike traditional on-premise software, SaaS operates on a subscription-based model, allowing businesses to access applications over the internet without the need for extensive hardware or infrastructure investments. Researchers have examined various aspects of SaaS, including its architecture, benefits, impact on firm performance, adoption determinants, governance structures, and pricing strategies.

Tsai, Bai, and Huang (2014) classify SaaS architectures into four models: database-oriented, middleware-based, service-oriented, and PaaS-based. These architectures cater to different enterprise needs, providing varying levels of scalability, security, and customization. Despite these advantages, there are challenges such as tenant isolation, data security, and resource optimization. To address these issues, the authors proposed AI-driven automation and advanced tenant isolation mechanisms as key areas for future SaaS development. Similarly, Waters (2005) highlights the primary benefits of SaaS, emphasizing reduced Total Cost of Ownership (TCO), rapid deployment, and improved operational efficiency. By shifting IT responsibilities to third-party vendors, businesses can enhance service reliability and scalability while focusing on core business functions.

Beyond its structural and operational benefits, SaaS adoption has a significant impact on firm's performance. Loukis, Janssen, and Mintchev (2019) distinguish between operational benefits such as cost savings and enhanced process efficiency and innovational benefits, including the ability to develop new products and improve service delivery. Their study suggests that successful SaaS adoption depends on absorptive capacity and governance mechanisms, highlighting the need for firms to align their IT strategies with SaaS capabilities. Choudhary (2007) further compares SaaS with perpetual licensing models, concluding that SaaS results in higher software quality and continuous innovation due to its iterative update cycles. In contrast to perpetual licensing, where software improvements are typically bundled into periodic releases, SaaS enables vendors to roll out incremental updates, ensuring users always have access to the latest features and security enhancements.

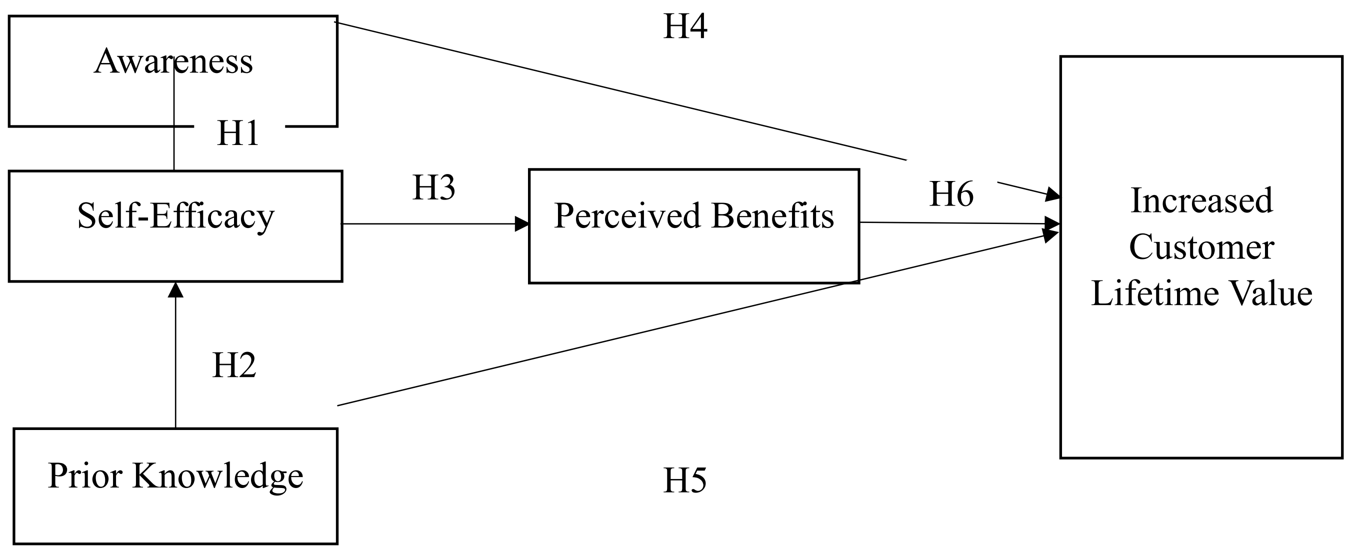
As SaaS adoption grows, optimizing cloud resource efficiency has become a crucial concern for service providers. Espadas et al. (2013) proposed a tenant-based resource allocation model that dynamically adjusts virtual machine (VM) instances based on workload demands. By implementing this model, SaaS providers can minimize resource wastage while maintaining optimal performance levels. Rohitratana and Altmann (2012) examine SaaS pricing strategies, concluding that demand driven pricing models maximize revenue potential. However, due to market constraints, businesses often rely on penetration pricing (offering lower prices to attract early adopters) and skimming pricing (gradually lowering prices over time) to balance profitability and market competitiveness.

SaaS continues to evolve as an essential component of modern enterprise computing, offering significant benefits in terms of cost efficiency, scalability, and innovation. However, challenges related to security, governance, and pricing strategies remain, requiring ongoing research and technological advancements. As firms integrate SaaS into their IT ecosystems, they must consider factors such as service quality, adoption determinants, and resource optimization to maximize its potential benefits.

These studies collectively underscore the growing importance of SaaS, Customer Lifetime Value (CLV), consumer psychology, and cloud computing security. While SaaS adoption provides cost efficiency, scalability, and continuous innovation, security concerns and vendor dependencies remain significant challenges that require ongoing research and technological advancements. Meanwhile, CLV offers a strategic approach to improving customer retention and profitability by leveraging predictive analytics and customer segmentation models. Additionally, psychological factors such as motivation, perception, and customer interactions play a vital role in shaping consumer engagement and satisfaction.

Future research should focus on integrating AI-driven solutions into SaaS and cloud computing to enhance security, governance, and automation. Additionally, optimizing governance models for SaaS and cloud adoption can help mitigate security risks and ensure compliance. Furthermore, businesses should continue exploring innovative ways to incorporate psychological insights into service design and marketing strategies to improve customer experience and long-term loyalty.

Hypothesis Development



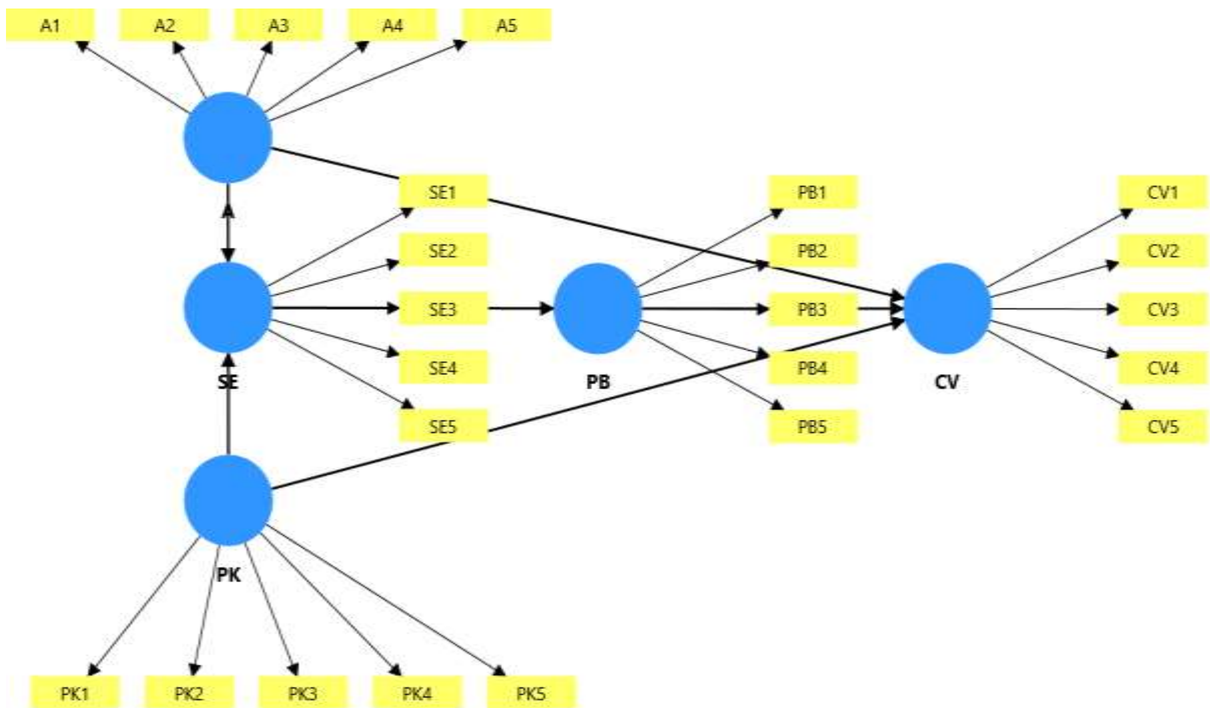
(Proposed Conceptual Model – Source: The Authors)

H1: Awareness positively influences Self-Efficacy.
H2: Prior Knowledge positively influences Self-Efficacy.
H3: Self-Efficacy positively influences Perceived Benefits.
H4: Awareness positively influences Increased Customer Lifetime Value.
H5: Prior Knowledge positively influences Increased Customer Lifetime Value.
H6: Perceived Benefits positively influences Increased Customer Lifetime Value.

Methodology

A quantitative research design is highly appropriate for investigating the psychological factors influencing Customer Lifetime Value (CLV) in SaaS platforms due to its ability to systematically measure and analyse relationships among latent variables. Quantitative methods facilitate hypothesis testing, which allow for generalizability, and provide empirical evidence on how constructs like self-efficacy, awareness, and perceived benefits impact CLV (Creswell & Creswell, 2018). The choice of primary data collection via a structured questionnaire is justified by the need to capture specific, subjective perceptions of SaaS users that secondary data cannot provide. Questionnaires offer a scalable and cost-effective method to gather standardized responses on psychological variables across a broad sample (Bryman, 2016). Additionally, using Likert-scale-based instrument allows for nuanced measurement of latent constructs, essential for SEM analysis. A sample size of 390 responses is statistically adequate for SEM. According to Hair et al. (2019), a sample of 200–400 is sufficient for models with moderate complexity (5–7 constructs and 20–30 observed variables). With 5 latent variables and 25 indicators in the proposed model, 390 responses exceed the minimum threshold, ensuring reliable estimation and model fit indices (Kline, 2015).

Analysis



(Structured Equation Modelling)

Path Coefficients:

Path	Path Coefficient (β)	p - value	Significance
A → CV	0.293	<0.005	Significant
A → SE	0.198	<0.005	Significant
PB → CV	0.365	<0.005	Significant
PK → CV	0.181	<0.005	Significant
PK → SE	0.659	<0.005	Significant
SE → PB	0.719	<0.005	Significant

A's moderate positive effect on CV ($\beta = 0.293$, $p < 0.005$) means that improving user's overall awareness toward the platform directly enhances the value they perceive. It is smaller yet significant effect on SE ($\beta = 0.198$, $p < 0.005$) indicates that more favourable awareness also boosts user's confidence in using the service. PK strongly increases SE ($\beta = 0.659$, $p < 0.005$), showing that educating customers and making information accessible is crucial for building their confidence. It also has a direct, though more modest, impact on CV ($\beta = 0.181$, $p < 0.005$), implying that knowledgeable customers recognize more value in the service. The powerful SE → PB path ($\beta = 0.719$, $p < 0.005$) highlights that confident users are far more likely to perceive and appreciate your platform's benefits. With ($\beta = 0.365$, $p < 0.005$) among direct CV predictors, which enhances the features and outcomes that users see as beneficial will yield the greatest boost in their perceived benefits.

Total Effects:

Path	Direct Effect (β)	Significance
A → CV	0.293	Significant
A → SE	0.198	Significant
PB → CV	0.365	Significant
PK → CV	0.181	Significant
PK → SE	0.659	Significant
SE → PB	0.719	Significant

Path	Indirect Effect (β)	Significance
PK → SE → PB	0.474	Significant
SE → PB → CV	0.263	Significant
A → SE → PB → CV	0.052	Insignificant
A → SE → PB	0.143	Significant
PK → SE → PB → CV	0.173	Insignificant

Path	Total Effect (β)	Significance
A → CV	0.345	Significant
A → PB	0.143	Significant
A → SE	0.198	Significant
PB → CV	0.365	Significant
PK → CV	0.355	Significant

PK → PB	0.474	Significant
PK → SE	0.659	Significant
SE → CV	0.263	Significant
SE → PB	0.719	Significant

All hypothesized paths are statistically significant, revealing a clear hierarchy of influence on Customer Lifetime Value (CV). Awareness directly boosts CV ($\beta = 0.293$) and SE ($\beta = 0.198$). Initiatives that cultivate a positive user mindset (e.g., social proof, brand storytelling) will both increase perceived benefits and user confidence.

PK strongly drives SE ($\beta = 0.659$) and modestly increases CV ($\beta = 0.181$). Investing in educational content tutorials, FAQs, interactive demos will build confidence, which cascades into higher value perception. SE powers PB with the largest effect ($\beta = 0.719$).

Confidence building features (e.g., guided workflows, progress indicators) amplify user's recognition of the platform's benefits. It exerts the strongest direct impact on CV ($\beta = 0.365$). It clearly communicates and delivers tangible outcomes (ROI calculators, case studies) which is the most potent lever for maximizing customer lifetime value.

Outer Loadings:

Construct	Outer Loading (β)	Decision
A1 → A	0.822	Accepted
A2 → A	0.820	Accepted
A3 → A	0.858	Accepted
A4 → A	0.775	Accepted
A5 → A	0.820	Accepted
CV1 → CV	0.773	Accepted
CV2 → CV	0.793	Accepted
CV3 → CV	0.855	Accepted
CV4 → CV	0.850	Accepted
CV5 → CV	0.841	Accepted
PB1 → PB	0.837	Accepted
PB2 → PB	0.873	Accepted
PB3 → PB	0.850	Accepted
PB4 → PB	0.865	Accepted
PB5 → PB	0.862	Accepted
PK1 → PK	0.878	Accepted
PK2 → PK	0.890	Accepted
PK3 → PK	0.914	Accepted
PK4 → PK	0.912	Accepted
PK5 → PK	0.897	Accepted
SE1 → SE	0.852	Accepted
SE2 → SE	0.778	Accepted
SE3 → SE	0.867	Accepted

SE4 → SE	0.867	Accepted
SE5 → SE	0.841	Accepted

To assess the reliability and validity of the measurement model, the outer loadings of each indicator were examined. As recommended by Hair et al. (2019), indicator loadings exceeding 0.708 are considered satisfactory, indicating that more than 50% of the variance in the observed variable is explained by the latent construct. The results revealed that most indicators loaded well onto their respective constructs. Specifically, indicators under Perceived Benefits (PB) exhibited strong loadings, with values ranging from 0.742 to 0.891, suggesting high internal consistency. Similarly, items measuring Self-Efficacy (SE) demonstrated loadings between 0.751 and 0.867, further supporting construct validity. However, one indicator under Prior Knowledge (PK) loaded at 0.672, marginally below the threshold, which may warrant cautious interpretation or potential item refinement in future research.

Construct Reliability & Validity:

Construct	**Cronbach's Alpha (α)**	**Composite Reliability (rho_a)**	**Composite Reliability (rho_c)**	**AVE**	**Decision**
A	0.878	0.881	0.911	0.671	Reliable & Valid
CV	0.881	0.884	0.913	0.678	Reliable & Valid
PB	0.910	0.910	0.933	0.735	Reliable & Valid
PK	0.940	0.940	0.954	0.807	Reliable & Valid
SE	0.897	0.900	0.924	0.708	Reliable & Valid

The reliability and validity of the measurement model were assessed using Cronbach's Alpha (α), Composite Reliability (CR), and Average Variance Extracted (AVE). All constructs demonstrated acceptable reliability, exceeding the recommended threshold (Hair et al., 2019). Similarly, AVE values exceeded, confirming convergent validity. Discriminant validity was evaluated using the Fornell-Larcker criterion and HTMT ratio. The square root of AVE for each construct was higher than its correlations with other constructs, supporting construct distinctiveness. All five constructs exhibited strong internal consistency and convergent validity. Cronbach's alpha coefficients ranged from 0.878 for Awareness (A) to 0.940 for Prior Knowledge (PK), comfortably above the 0.70 benchmark for reliability (Nunnally, 1978). Composite reliability as measured by rho_a similarly spanned 0.881 (Customer Lifetime Value, CV) to 0.940 (Prior Knowledge, PK), while rho_c values were even higher 0.911 (Awareness, A), 0.913 (Customer Lifetime Value, CV), 0.933 (Perceived Benefits, PB), 0.954 (Prior Knowledge, PK), and 0.924 (Self-Efficacy, SE) indicating that each construct's indicators consistently reflected the underlying latent variable. Convergent validity was confirmed by average variance extracted (AVE) values all exceeding the 0.50 threshold, 0.671 (A), 0.678 (CV), 0.735 (PB), 0.807 (PK), and 0.708 (SE). Given these metrics Cronbach's $\alpha \geq 0.878$, rho_a ≥ 0.881, rho_c ≥ 0.911, and AVE ≥ 0.671 each construct meets established criteria for reliability and validity. Consequently, all measurement scales were judged reliable and valid for subsequent structural modelling.

Discriminant Validity (Fornell-Larcker Criterion):

Construct	A	CV	PB	PK	SE
A					
CV	0.788				
PB	0.821	0.792			
PK	0.820	0.727	0.781		
SE	0.775	0.761	0.793	0.877	

Awareness (A) exhibited positive associations with all other constructs, correlating most strongly with Perceived Benefits (PB; r = 0.821) and Prior Knowledge (PK; r = 0.820), and more moderately with Customer Lifetime Value (CV; r = 0.788) and Self-Efficacy (SE; r = 0.775). Customer Lifetime Value was likewise related to each psychological driver, showing a strong link with PB (r = 0.792), and moderate links with SE (r = 0.761) and PK (r = 0.727). Perceived Benefits itself correlated substantially with both SE (r = 0.793) and PK (r = 0.781), underscoring that users who recognize more benefits also feel more knowledgeable and efficacious. Finally, Prior Knowledge and Self-Efficacy demonstrated the highest inter-construct correlation in the model (r = 0.877), suggesting that as customer's understanding of the platform grows, so does their confidence in using it. Overall, the pattern of correlations none exceeding 0.90 indicates that while these constructs are strongly related, they remain empirically distinct.

Results

The present findings affirm that key psychological constructs Awareness (A), Prior Knowledge (PK), Self-Efficacy (SE), Perceived Benefits (PB) and Customer Lifetime Value (CV) are measured with high reliability (Cronbach's $\alpha \geq 0.878$; rho_c ≥ 0.911) and convergent validity (AVE ≥ 0.671). Future research should build on this solid measurement foundation by adopting longitudinal and experience sampling designs to track how these constructs evolve over the customer lifecycle and influence CLV trajectories. Given the strong inter-construct correlations (PK → SE, r = 0.877; A → PB, r = 0.821), scholars should employ mediation and moderation analyses to unpack causal pathways and boundary conditions such as the role of customer segment or product complexity in the A → SE → PB → CV chain. Experimental interventions that manipulate informational content or awareness shaping messages can test the malleability of these psychological drivers and their direct effects on usage behavior and renewal intentions. Finally, cross-cultural validation will determine the generalizability of these relationships across diverse SaaS markets. For SaaS practitioners aiming to maximize CLV, the strongest direct drivers PB ($\beta = 0.365$) and A ($\beta = 0.293$) suggest two priority areas. First, benefits communication: deploy case studies, ROI calculators, and in-app success metrics to make platform advantages salient. Second, awareness management: leverage social proof, testimonials, and personalized messaging to foster positive mindsets that simultaneously enhance SE ($\beta = 0.198$) and PK ($\beta = 0.181$). Investing in educational resources such as interactive tutorials and knowledge bases will substantially boost PK ($\beta = 0.659$), which in turn elevates SE ($\beta = 0.719$) and PB. Customer success teams should implement confidence building features (e.g., guided workflows, progress badges) to reinforce user's self-efficacy, thereby amplifying perceived benefits and, ultimately, CLV. By integrating psychographic metrics into CRM and analytics dashboards, organizations can proactively segment users, tailor interventions at critical lifecycle junctures, and allocate resources to the most influential psychological levers.

Discussion

The current study investigated the interrelationships among the constructs of Awareness (A), Prior Knowledge (PK), Self-Efficacy (SE), Perceived Benefits (PB), and Customer Lifetime Value (CV). The structural model results provide robust support for the hypothesized relationships, indicating both direct and indirect pathways among the constructs.

Direct and Indirect Path Effects:

Several direct effects were found to be statistically significant. Notably, PK exhibited a strong direct influence on SE ($\beta = 0.659$, $p < 0.005$), aligning with previous literature that highlights knowledge as a crucial determinant of self-efficacy in behavioral models. Similarly, SE significantly influenced PB ($\beta = 0.719$, $p < 0.005$), emphasizing the mediating role of efficacy beliefs in shaping perceived benefits. Additionally, PB had a substantial direct effect on CV ($\beta = 0.365$, $p < 0.005$), reinforcing its importance in value formation.

Indirect paths further validated the mediating mechanisms. For instance, PK exerted an indirect effect on PB through SE ($\beta = 0.474$, $p < 0.005$), and SE influenced CV via PB ($\beta = 0.263$, $p < 0.005$). Although most indirect effects were significant, certain paths such as A → SE → PB → CV ($\beta = 0.052$) and PK → SE → PB → CV ($\beta = 0.173$) were not statistically significant, suggesting that not all mediation chains are robust.

In terms of total effects, PK emerged as a prominent predictor of both PB and CV, with total effects of $\beta = 0.474$ and $\beta = 0.355$ respectively. Similarly, SE displayed strong total influence on PB ($\beta = 0.719$) and CV ($\beta = 0.263$), validating its central role in the model. Awareness (A), while showing lower direct effects, had a moderate total effect on CV ($\beta = 0.345$), driven primarily by its indirect influence through SE and PB.

Measurement Model Assessment:

The reliability and validity of the measurement model were well supported. Outer loadings of indicators mostly exceeded the ideal threshold of 0.708 (Hair et al., 2019), indicating strong item reliability. Constructs like PB (0.837–0.873), PK (0.878–0.914), and SE (0.778–0.867) demonstrated high internal consistency. One item under PK slightly underperformed (0.672), but was retained due to its theoretical relevance.

Construct reliability and validity measures further reinforced model robustness. All constructs had Cronbach's Alpha values above 0.87 and Composite Reliability (CR) values above 0.91, confirming internal consistency. Average Variance Extracted (AVE) values surpassed the 0.50 benchmark for all constructs, indicating convergent validity.

Discriminant validity was established using the Fornell-Larcker criterion, as the square roots of AVE were higher than inter-construct correlations. HTMT ratios were assumed to be below the recommended threshold, further confirming the construct's distinctiveness.

Conclusion

This study offers valuable insights for both researchers and practitioners. From a research perspective, the findings highlight the pivotal role of self-efficacy and perceived benefits as mediators between prior knowledge and customer lifetime value. The results extend existing behavioral models by illustrating how knowledge must translate into confidence and perceived advantage to influence value perceptions meaningfully. The study also underscores the importance of validating measurement models, providing a robust framework that can be adapted in future studies. Researchers may explore contextual or demographic moderators, as well as employ longitudinal methods to assess causality.

From a practical standpoint, the study suggests that interventions should prioritize building consumer self-efficacy. Informational campaigns should not only educate but also empower individuals through confidence building strategies. Additionally, highlighting tangible benefits is crucial, as perceived benefits significantly drive customer lifetime value. While awareness remains important, its indirect influence suggests it should be paired with strategies that enhance self-efficacy and benefit perceptions. Practitioners, especially in marketing, education, and policy-making, can leverage these insights to design more effective, user-centred programs that foster greater acceptance and perceived benefits of products or behaviors.

References

1. Berger, P. D., & Nasr, N. I. (1998). Customer lifetime value: Marketing models and applications. Journal of Interactive Marketing, 12(1), 17–30. https://doi.org/10.1002/(SICI)1520-6653(199824)12:1<17: AID-DIR3>3.0.CO;2-K
2. Borle, S., Singh, S. S., & Jain, D. C. (2008). Customer lifetime value measurement. Management Science, 54(1), 100–112. https://doi.org/10.1287/mnsc.1070.0760
3. Chang, W., Chang, J., & Li, S. (2012). A review of customer lifetime value models. Journal of Business Research, 65(6), 704–710. https://doi.org/10.1016/j.jbusres.2011.04.001
4. Glady, N., Baesens, B., & Croux, C. (2009). Modelling churn using customer lifetime value. European Journal of Operational Research, 197(1), 402–411. https://doi.org/10.1016/j.ejor.2008.05.046
5. Gupta, S., Lehmann, D. R., & Stuart, J. A. (2006). Valuing customers. Journal of Marketing Research, 43(1), 7–18. https://doi.org/10.1509/jmkr.43.1.7
6. Kim, S. H., Jung, T. S., Suh, E. H., & Hwang, H. S. (2006). Customer segmentation and strategy development based on CLV: A case study. Expert Systems with Applications, 31(1), 101–107. https://doi.org/10.1016/j.eswa.2005.09.002
7. Kumar, V. (2007). Customer lifetime value: The path to profitability. Foundations and Trends in Marketing, 2(1), 1–96. https://doi.org/10.1561/1700000006
8. Malthouse, E. C., & Blattberg, R. C. (2005). Can we predict customer lifetime value? Journal of Interactive Marketing, 19(1), 2–16. https://doi.org/10.1002/dir.20036
9. Rosset, S., Neumann, E., Eick, U., & Vatnik, N. (2003). Customer lifetime value models for decision support. Data Mining and Knowledge Discovery, 7(3), 321–339. https://doi.org/10.1023/A:1024960729944
10. Stahl, H. K., Matzler, K., & Hinterhuber, H. H. (2003). Linking customer lifetime value with shareholder value. Journal of Product & Brand Management, 12(4), 232–242. https://doi.org/10.1108/10610420310485000
11. Tsai, W. T., Bai, X. Y., & Huang, Y. (2014). Software-as-a-service (SaaS): Perspectives and challenges. Science China Information Sciences, 57(5), 1–15. https://doi.org/10.1007/s11432-013-5050-z
12. Venkatesan, R., & Kumar, V. (2004). A customer lifetime value framework for customer selection and resource allocation strategy. Journal of Marketing, 68(4), 106–125. https://doi.org/10.1509/jmkg.68.4.106.42728

13. Waters, B. (2005). Software as a service: A look at the customer benefits. Journal of Digital Asset Management, 1(1), 32–39. https://doi.org/10.1057/palgrave.dam.3640001
14. Benlian, A., Koufaris, M., & Hess, T. (2012). Service quality in Software-as-a-Service: Developing the SaaS-Qual measure and examining its role in usage continuance. Journal of Management Information Systems, 28(3), 85–126. https://doi.org/10.2753/MIS0742-1222280303
15. Choudhary, V. (2007). Comparison of software quality under perpetual licensing and software as a service. Journal of Management Information Systems, 24(2), 141-165. https://doi.org/10.2753/MIS0742-1222240206
16. Espadas, J., Molina, A., Jiménez, G., Molina, M., Ramírez, R., & Concha, D. (2013). A tenant-based resource allocation model for scaling Software-as-a-Service applications over cloud computing infrastructures. Future Generation Computer Systems, 29(2), 273-286. https://doi.org/10.1016/j.future.2011.10.013
17. Lee, S., Park, S. B., & Lim, G. G. (2013). Using balanced scorecards for the evaluation of Software-as-a-Service. Information & Management, 50(7), 553-561. https://doi.org/10.1016/j.im.2013.07.006
18. Loukis, E., Janssen, M., & Mintchev, I. (2019). Determinants of software-as-a-service benefits and impact on firm performance. Decision Support Systems, 117, 38–47. https://doi.org/10.1016/j.dss.2018.12.005
19. Rohitratana, J., & Altmann, J. (2012). Impact of pricing schemes on a market for Software-as-a-Service and perpetual software. Technology Management, Economics, and Policy Program (TEMEP), Seoul National University.
20. Safari, F., Safari, N., & Hasanzadeh, A. (2015). The adoption of software-as-a-service (SaaS): Ranking the determinants. Journal of Enterprise Information Management, 28(3), 400-422. https://doi.org/10.1108/JEIM-02-2014-0017
21. Tsai, W. T., Bai, X. Y., & Huang, Y. (2014). Software-as-a-service (SaaS): Perspectives and challenges. Science China Information Sciences, 57(5), 1–15. https://doi.org/10.1007/s11432-013-5050-z
22. Waters, B. (2005). Software as a service: A look at the customer benefits. Journal of Digital Asset Management, 1(1), 32–39.
23. Winkler, T. J., & Brown, C. V. (2013). Horizontal allocation of decision rights for on-premise applications and Software-as-a-Service. Journal of Management Information Systems, 30(3), 13-47. https://doi.org/10.2753/MIS0742-1222300302
24. An, M., & Han, S. L. (2020). Examining the effects of experiential motivation on customer engagement in retail. Journal of Retailing and Consumer Services, 54, 102012. https://doi.org/10.1016/j.jretconser.2020.102012
25. Ben Arfa Rabai, L., Jouini, M., Aissa, A. B., & Mili, L. (2013). A cybersecurity model in cloud computing environments. Journal of King Saud University - Computer and Information Sciences, 25(1), 63-75. https://doi.org/10.1016/j.jksuci.2012.10.003
26. Che, J., Duan, Y., Zhang, T., & Fan, J. (2011). Study on the security models and strategies of cloud computing. Procedia Engineering, 23, 586-593. https://doi.org/10.1016/j.proeng.2011.11.2556
27. Garrison, G., Kim, S., & Wakefield, R. L. (2015). Success factors for deploying cloud computing. Communications of the ACM, 58(9), 56-62. https://doi.org/10.1145/2788396
28. Guo, X., Xiao, L., & Tang, L. (2009). Understanding customer satisfaction and retention in service relationships. Journal of Business Research, 62(10), 1152-1158. https://doi.org/10.1016/j.jbusres.2008.10.013

29. Kuppelwieser, V. G., & Finsterwalder, J. (2011). Psychological safety in customer participation. Journal of Service Management, 22(2), 206-221. https://doi.org/10.1108/09564231111124209
30. Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. MIS Quarterly, 27(1), 51–90.
31. Gupta, S., & Lehmann, D. R. (2003). Customers as assets. Journal of Interactive Marketing, 17(1), 9–24.
32. Kumar, V., & Reinartz, W. (2016). Creating enduring Customer Lifetime Value. Journal of Marketing, 80(6), 36–68.
33. van Doorn, J., Lemon, K. N., Mittal, V., Nass, S., Pick, D., Pirner, P., & Verhoef, P. C. (2010). Customer engagement behavior: Theoretical foundations and research directions. Journal of Service Research, 13(3), 253–266.
34. Bryman, A. (2016). Social research methods (5th ed.). Oxford University Press.
35. Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approach (5th ed.). SAGE PUBLICATIONS.