Journal of Business Research 164 (2023) 114001

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Customer engagement with digitalized interactive platforms in retailing

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ARTICLE INFO

Keywords:
Customer engagement
Digitalized interactive platform
Subjective well-being
SEM-ANN
Self-determination theory
Service dominant logic

ABSTRACT

Digitalized interactive platforms (DIPs) such as Apple watch, Starbucks apps and Nike^{+} have seen enormous growth. This study empirically investigates the antecedents and consequences of customer engagement in a digitalized interactive platform of an online shoe retailing start-up. Specifically, we integrate service-dominant logic and self-determination theory to explore the complex relationships between human psychological needs, customer engagement and subjective well-being. We hypothesise that, in case of digitalized interactive platforms, the direct relationship between human psychological needs satisfaction (autonomy, relatedness and competence) and subjective well-being is mediated by customer engagement (cognitive, affective and behavioral). We applied a hybrid SEM-ANN approach to unravel the relationships. Findings show that autonomy and competence have significant relationships with all the dimensions of customer engagement (cognitive, affective and behavioral). Results also show that subjective well-being is not influenced by cognitive engagement but is influenced by affective and behavioral engagement. Theoretical and managerial contributions are discussed.

1. Introduction

Retailers are increasingly re-conceptualising their offerings, processes, and interfaces holistically to design digitalized interactive platforms (hereafter, DIPs) for creating value through interactions (He & Zhang, 2022). A retail offering positioned as a DIP highlights a networked arrangement of four dimensions; namely artifact, persons, processes, and interfaces (APPI), thereby resulting in the development of multiple interactive system environments that are capable of empowering actors to engage in interactional value creation (Ramaswamy & Ozcan, 2018a, 2018b). For instance, Apple retail stores act as a DIP that institutes APPI to facilitate customer engagement. Specifically, products on in-store display are represented as artifacts capable of enabling playful interaction and enjoyment among potential customers, thereby enabling customer engagement. Further, the Apple store as a DIP is configured for ordinary people, where the focus is on customer experience and not on the predominant practice of disseminating information about the features of products, typically adopted by most technology companies. Specifically, Apple invites potential customers to engage with its products, and experience them to play, explore, and discover entertainment, productivity, and lifestyle media. Within its store, Apple also facilitates a digital concierge process, available in both self-service and employee-assisted modes, that directs customers to different sections of the store, allows them to scan the barcodes of accessories in the store, get reviews, ratings and products specs and pay for purchases within the app through Apple Pay using the self-checkout option. Further, Apple manages the physical App Store as a DIP '*with multiple connective other assemblages entailing books, music, videos, and credit card accounts to enable a variety of novel, personalized, co-creational experiences*' (Ramaswamy & Ozcan, 2019, p.22). This suggests that DIPs can help traditional firms accomplish digital transformation (He & Zhang, 2022). Other notable examples of brands offering DIPs include Burberry, Starbucks, Amazon and others (Ramaswamy & Ozcan, 2019). With more and more brands investing in DIPs, Servion Global Solutions predicts that by 2025, ninty five per cent of customer-firm interactions will be powered by technologies including DIPs, and without human involvement (Ed Lauder, 2017). Therefore, as predicted by Forbes, DIP-enabled customer engagement is likely to increase in the future and eventually

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https://doi.org/10.1016/j.jbusres.2023.114001
Received 20 November 2022; Received in revised form 23 April 2023; Accepted 24 April 2023
Available online 4 May 2023

replace human-to-human interactions in a transformational way (Morgan, 2018; Hollebeek et al., 2021).

With the deployment of DIPs, one area being transformed is value creation. Conventionally, retailers and customers had distinct roles in the process of retail value creation (Mostaghel et al., 2022). Specifically, retailers viewed customers' roles as limited to passive recipients of retailers' offerings. With the proliferation of DIPs in retail, the preferences in customers' shopping have transitioned from purchasing products, through receiving services, to becoming engaged actors within the retail ecosystem (Ramaswamy & Narayanan, 2022 press; Ramaswamy & Ozcan, 2019). With the proliferation of digital technologies in the retailing, customers have become active co-creators of their own experiences through continuous ongoing interactions. Value is created because of these ongoing interactions in a joint space between customers, retailers, and the associated retail ecosystems (He & Zhang, 2022). Therefore, customer engagement (CE), an inherently interactive and reciprocal concept, can act as a prominent mechanism to examine customers' relationship with DIPs (Hollebeek & Belk, 2021).

The significant body of CE research maintains a consensus that CE is a 'context-specific' phenomenon (Hollebeek et al., 2021). Building on this notion, the literature offers a clear understanding of how CE with brands is enabled through digital contexts, including social media, virtual/augmented/mixed reality-, gamification-, digital content marketing-, and artificial intelligence-based applications, to name a few (e.g., Huang & Rust, 2021; Singh et al., 2021; Hollebeek & Macky, 2019). Despite these advances, there are several gaps. First, most research focuses on the brand as the focal object of CE (Hollebeek et al., 2021). However, the literature acknowledges that CE can go beyond dyadic interactions with a brand (Alexander et al., 2018). Indeed, customers often direct their engagement to multiple actors (Brodie, et al., 2019; Roy et al., 2018; Verleye et al., 2014; Vo-Thanh et al., 2021). This multi-actor engagement situation is integral to the context of DIPs (Novak & Hoffman, 2019; Hoffman & Novak, 2018; Apostolidis et al., 2021), noting that DIPs refer to a networked configuration of artifacts, persons, processes, and interfaces (Ramaswamy & Ozcan, 2018a, 2018b). Therefore, we treat DIPs as the primary objects of engagement. This proposed conceptualisation of DIP-enabled CE is rooted in service-dominant logic (S-DL) (Vargo & Lusch, 2008, 2016), which considers CE as an interactive experience between a customer and an object (Hollebeek et al., 2014). With DIPs considered as the focal objects of engagement, the processes around the interaction mechanism require a deeper understanding (Novak & Hoffman, 2017). Second, despite research investigating the nature of CE through a range of digital channels, little research has gone beyond channel-specific findings. Our focus on DIP-enabled CE provides a more holistic picture, which is relevant to the majority of brands that operate across multiple channels.

We draw on self-determination theory (SDT) to explain how customers interact with DIPs. SDT highlights the satisfaction of three basic human psychological needs: autonomy (feeling unforced in one's actions and following one's goals and values), competence (feeling able and effective), and relatedness (feeling connected to others, a sense of belonging) (ARC) (Deci & Ryan, 2000). SDT is a macro theory that reveals the relationships between motivation, psychological needs satisfaction, and well-being in social environments (Deci & Ryan, 2000). However, we assume that, in the context of DIPs, the direct relationship between human psychological needs satisfaction and subjective well-being is mediated by CE. The more customers' needs for autonomy, competence and relatedness are satisfied, the more they will feel self-determined in the regulation of their behaviors, resulting in greater engagement with the DIPs. Thus, in SDT terms, where needs fulfilment enhances well-being, co-creational interactions can contribute to the subjective well-being of customers, and this will be stronger when purposeful attention is given to how DIPs can support customers' needs for autonomy, competence, and relatedness (Engström & Elg, 2015; Wang, Lin, & Spencer, 2019). We argue that satisfaction of customers' needs for autonomy, competence and relatedness have the potential to impact value co-creation activities (based on S-DL). The literature in turn is replete with examples supporting that need-satisfaction in these areas contribute positively to wellbeing. However, limited attention has gone into integrating the SDT and S-DL perspectives to examine the positive relationship between need satisfaction, co-creation, and well-being. Thus, this study has twofold objective:

1. To investigate the antecedents and consequences of DIP-enabled customer engagement.
2. To test the mediating role of DIP-enabled customer engagement between need satisfaction (autonomy, relatedness, and competence) and customers' subjective well-being.

This study makes several key contributions. First, this study applies SD-Logic to understand DIP-enabled CE. Second, it integrates basic needs theory, a sub-set of SDT, to conceptualise and empirically validate the antecedents and consequences of DIP-enabled CE. Specifically, we unravel the complex relationships between human psychological needs (autonomy, relatedness and competence), customer engagement (cognitive, affective and behavioral) and subjective well-being. Third, two-phased multi-analytical models were used: SEM for evaluating the impact of psychological needs satisfaction on DIP-enabled CE and subjective well-being, and artificial neural network (ANN) analysis for the validation of SEM outcomes and predicting the significance of the key relationships. This combined approach provides a holistic understanding of the topic and, equally important, the disadvantages of one approach can be offset by the advantages of the other (Scott & Walczak, 2009). The findings have important implications for managers, particularly for those operating DIPs in their service settings.

The organization of the remainder of this paper is laid out as follows. The subsequent sections present the review of literature. Then, the research model and hypothesis are detailed, followed by methodology, data analysis techniques and statistical results. The subsequent sections detail discussion, managerial and theoretical contributions. Finally, the paper rounds up with limitations and direction for future studies.

2. Literature review

2.1. Customer engagement with DIPs

For several years, CE has been a topic of interest among researchers and practitioners (Brodie et al., 2011; Pansari & Kumar, 2017; de Oliveira Santini et al., 2020). There is still an ongoing debate on the conceptualisation and dimensionality of customer engagement (Hollebeek et al., 2021). Grounded in different theoretical underpinnings, one group of scholars argues that CE is comprised of both in-role and extra-role customer cognitions, emotions, and behaviors (Harrigan et al., 2018; Kumar et al., 2019). By contrast, other groups of scholars restrict CE to those expressions that are primarily extra-role in nature (Van Doorn et al., 2010). In this study, we adopt the former conceptualisation of CE that offers a more holistic view of CE (Hollebeek et al., 2019; Groeger et al., 2016).

Van Doorn et al., (2010, p. 254) consider CE as unidimensional, focusing much on the behavioral aspect of CE and conceptualising it as "*the customer's behavioral manifestation toward a brand or firm, beyond purchase, resulting from motivational drivers.*" On the contrary, CE has been conceptualised as a multidimensional construct encompassing cognitive, affective and behavioral dimensions (Hollebeek et al., 2019; Brodie et al., 2011; Islam et al., 2019). For instance, Hollebeek et al., (2019, p. 167) define CE as a customer's "*investment of cognitive, emotional, behavioral, and social operant, and operand resources in their brand interactions.*" Similarly, Brodie et al. (2013, p 107) define CE as "*a multidimensional concept comprising cognitive, emotional, and/ or behavioral dimensions [that] plays a central role in the process of relational exchange.*" Consistent with these viewpoints, we posit that DIP-enabled CE comprises of cognitive, emotional, and behavioral dimensions. In the

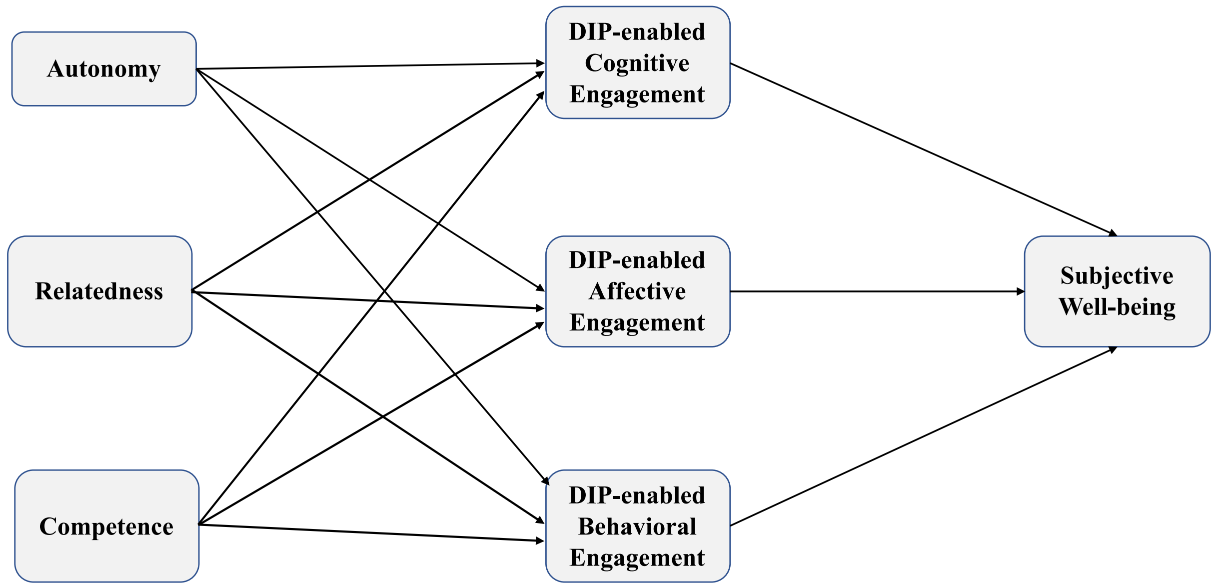

Fig. 1. Research Model.

context of DIPs, the cognitive dimension refers to customers' mental processing related to interactions with DIPs. The affective dimension describes the degree of emotions customers experience towards the DIPs. Finally, the behavioral dimension is defined as the customers' amount of energy, time, and effort allocated to their interactions with the DIPs (Hollebeek et al., 2014). Specifically, it is presumed that in their interactions with DIPs, customers are more likely to invest effort (behavior) to maintain interactions, be mentally engrossed (cognitive) in their interactions, and be enthusiastically inspired (affective) in the process of interactions (Dwivedi, 2015).

Thus, CE is an interactive concept that emerges during customer-object [DIP] interactions (Harrigan et al., 2018). During these interactions, CE represents customers' resource investments (Behnam et al., 2021). For example, customers may use their devices (i.e., operand resource) along with their cognitive skills (i.e., operant resource) to interact with the DIPs (Islam et al., 2019). Based on the preceding discussions, we consider DIP-enabled customer engagement through the S-D logic perspective.

3. Research model and hypotheses

Following our review, we propose a conceptual model (Fig. 1) and related research hypotheses.

3.1. Autonomy, relatedness and competence (ARC) and customer engagement (CE)

The advent of DIPs has motivated customers to progressively engage with such platforms. SDT offers the motivational foundation to understand CE (Reeve, 2012). While other motivation theories examine how expectations, beliefs, and goals influence CE, SDT is distinct in that it focuses on the instructional task of stimulating inner motivational resources to enable CE (Reeve & Halusic, 2009). That is, SDT identifies the inner motivational resources that all customers hold, and it guides retailers to involve, foster, and energize these customer resources to facilitate engagement while interacting with the DIPs (Niemiec & Ryan, 2009).

Basic needs theory, one of the mini theories of SDT identifies the three psychological needs of customers (i.e., autonomy, relatedness, and competence) and categorises these as inherent inner motivational resources imperative to facilitate CE (Reeve, 2012). Autonomy is the psychological need to feel that one's actions and behaviors are self-chosen, self-governed, and self-endorsed (Deci & Ryan, 1985; Loroz & Braig, 2015). Competence reflects the need to be effective while interacting with the environment. It showcases customers' inherent aspiration to employ one's capacities and, in doing so, to seek out and manage environmental challenges (Deci, 1975). Relatedness represents the psychological need to form close emotional attachments and responsive relationships (Deci & Ryan, 1991), thereby highlighting the need to feel connected to others (Deci & Ryan, 2000). Overall, relatedness is believed to increase the sense of belongingness and enables the process of internalization (Deci & Ryan, 2000). Sense of belongingness is considered a fundamental psychological need (Baumeisterop & Leary, 1995) as it is essential in establishing and sustaining strong relationships with others (Maunder, 2018). There is a consensus in literature that sense of belonging is a basic human need and a fundamental motivation, sufficient to drive behaviors and perceptions (Strayhorn, 2008). This is primarily related to the 'relatedness need' of ARC. Individuals tend to internalize the values and practices of those with whom they are connected, thereby enabling CE (Deci & Ryan, 2000). In summary, SDT identifies three basic needs, and the satisfaction of these needs is known to increase CE (Peters et al., 2018).

Previous studies have argued that the design of digital platforms influence (vs. inhibit) CE (Lim & Rasul, 2022). Specifically, the existing studies claim that platforms designed to require greater effort expectancy and those that entail higher risks (e.g., privacy concerns) to customers are likely to deter CE, whereas platforms that can perform as expected and that can provide enjoyment in a trustworthy manner will motivate customers to engage with the technological platform (Al Mamun et al., 2020; Quach et al., 2020). Similarly, He & Zhang (2022) posit that value created by DIPs directly influences customer engagement. This is consistent with the propositions of SD-Logic which states that value is always co-created by multiple actors including the beneficiary (Vargo & Lusch, 2016). Based on SDT, the present study deviates and add to this ongoing conversation by theorising that by tweaking the design of DIPs through the lens of ARC, CE can be influenced. Thus, satisfying the three basic needs of ARC through the functions, features and contents of DIPs will influence CE (Peters et al., 2018). This rationale is based on the premise that technology designs support or undermine basic psychological needs, thereby increasing engagement (Peters et al., 2018; Kim & Drumwright, 2016). For instance, DIPs may provide autonomy to its customers by providing them with choices, which would foster their understanding and interest in the DIPs, and encourage them to think independently and critically (Assor et al., 2002). Likewise, researchers have argued that when customers have a sense of belongingness and when they have the freedom to express their opinions, they are more likely to engage with the brand/object (Chan et al., 2014). Furthermore, authors have found that competence needs satisfaction has a strong connection with attachment, thereby enabling CE (Loroz & Braig, 2015). Consistent with the above theoretical support, the fulfilment of customers' needs for competence, relatedness and autonomy can serve as an impetus to action of engaging with the DIPs (Bauer et al., 2019). Since fulfilment of SDT's three psychological needs of competence, relatedness and autonomy are universal in nature. The extent to which these needs of people are satisfied, they will be intrinsically motivated to engage in extra-role behaviors. Therefore, we hypothesise the following:

H1: (a) Autonomy, (b) relatedness and (c) competence have direct and positive impacts on DIP-enabled cognitive engagement.
H2: (a) Autonomy, (b) relatedness and (c) competence have direct and positive impacts on DIP-enabled affective engagement.
H3: (a) Autonomy, (b) relatedness and (c) competence have direct and positive impacts on DIP-enabled behavioral engagement.

3.2. Mediating role of customer engagement

Diener, Scollon, and Lucas (2009) define subjective well-being (SWB) as a domain of behavioral science that allows individuals to evaluate their lives and includes concepts ranging from momentary mood to overall life satisfaction and from depression to unwarranted excessive happiness. SWB is an individual's emotional reactions to events and cognitive judgements of satisfaction and fulfilment (Diener et al., 2009). Prentice and Loureiro (2018) note that experience of pleasant and exciting emotions together with greater life satisfaction and lower negative moods is indicative of SWB. Prior study report that customers' likelihood of experiencing positive experience contribute to SWB (Zhou et al., 2022). According to SDT, the satisfaction of three basic needs (i.e., ARC) are imperative to enhancing an individual's SWB (Shulga & Busser 2021).

Empirical evidence suggests that helping others directly or indirectly has a positive impact on an individual's SWB (Cherrier & Munoz, 2007). As CE includes customers' extra-role behaviors, such as helping other customers and providing feedback to the DIPs operators, it may have a positive effect on customers' subjective well-being (SWB), which reflects an individual's self-evaluation of his or her quality of life (Diener, Lucas, & Oishi 2018). This is because people's perceived happiness is higher when they socialize and have close relationships with others (Kasser & Sheldon, 2002; Liu & Aaker, 2008). Thus, when the DIPs enable customers to socialise and help others, then these activities are likely to lead to an increased levels of satisfaction about one's life which in turn reflects in higher level of SWB. For example, prior studies show that engaging with live stream services for e-sports (i.e., a form DIP where interactions among players occur) is positively related to SWB (Kim & Kim, 2020). Specifically, players who engage with e-sports feel better about themselves and develop a more positive view of their own selves, ultimately resulting in SWB (Raggiotto & Scarpi, 2022). Based on this notion it is argued that customer engagement is likely to create and sustain positive feelings which contribute to their SWB (Mathis et al., 2016).

Prior studies suggest that SWB is the result of cognitive and affective evaluation of one's own life events (Tuan et al., 2023), whereas CE represents the psychological state of the customers during the interactive service experience process with a focal object (Brodie et al., 2011; Japutra et al., 2022). A greater level of DIP enabled customer engagement behaviors (i.e., cognitive, affective and behavioral) clearly reflects customer's satisfaction (i.e., a psychological state) with ARC needs fulfilment by the DIPs. As satisfaction is positively related to SWB (Su et al., 2018), it can be hypothesised that the relationship between ARC and SWB, while interacting with the DIPs, is mediated by CE. Based on the preceding discussions, we advance the following hypotheses:

H4: DIP-enabled cognitive engagement mediates the relationship between (a) autonomy, (b) relatedness, (c) competence and subjective well-being.
H5: DIP-enabled affective engagement mediates the relationship between (a) autonomy, (b) relatedness, (c) competence and subjective well-being.
H6: DIP-enabled behavioral engagement mediates the relationship between (a) autonomy, (b) relatedness, (c) competence and subjective well-being.

4. Methodology

4.1. Research setting

This study uses the text-based scenario to describe the real case of a European shoe retailer PIKKPACK that qualifies for the APPI criterion to be designated as DIP (Ramaswamy & Ozcan, 2018a, 2018b).

- A (Artifact)- Unassembled shoe materials
- P (People)- Employees managing the in-store experience, online support, other groups of people that customers can interact with to co-create value
- P (Process)- Selecting between shoe colour, sole material along with different types of shoelaces
- I (Interfaces)- Technological interface that allowed customisation

Text scenario-based design has been increasingly accepted in scholarly business studies because it offers greater realism (Henkens et al., 2021) and presents standardized stimuli to all participants, increasing the internal validity, measurement reliability, and ease of replication (Hyman & Steiner, 1996). Also, its ability to overcome constraints associated with examining real business situations (Fritzsche, 1988) (e.g., time, expense) increases its acceptance among business scholars.

The scenario describes the case of a Hungary-based shoe start-up PIKKPACK that configured its retail offerings as DIPs. The PIKKPACK DIPs enable its customers to edit and design shoes that otherwise are not available in the regular market. Further, the possibility of selecting from shoe colour to sole material along with different types of shoelaces through its DIP results in a plethora of shoe permutations. The PIKKPACK DIPs allow customers to seek any relevant product information, including its use in different climatic conditions, country of origin, and how to wash the shoes. PIKKPACK also maintains an appointment-based showroom for its users to physically create and experience the product. The ability of PIKKPACK to comply with all the DIP prerequisites makes it an appropriate research context for this study.

To reduce confounding effects and determine scenario-based realism, the scenario script was tested as follows (Tombs & McColl-Kennedy, 2013). First, the scenario was developed to ensure it meets the criterion to qualify as DIP. Second, the scenario was tested by using an expert panel comprising marketing professors from a leading Business School in Australia. The complete text scenario and related snapshot are shown in Appendix A. Further, the realism of the scenario was tested empirically using the following three-item scale (Henkens et al., 2021): (1) What is described in this scenario could also happen in real life, (2) the scenario seems realistic, and (3) I had no difficulty imagining myself in the situation.

4.2. Sample and data collection

Data was gathered using Mechanical Turk (MTurk) between June – August 2022. The following recommendations to set up MTurk were followed (a) paying an appropriate remuneration to motivate customers to fill out the questionnaire accurately (i.e., $2), (b) paying every customer even if the results could not be used, and (c) setting an

Table 1
Measurement items.

Construct (Source)	Measurement Item
Cognitive engagement (Hollebeek et al., 2011)	Using PIKKPACK gets me to think about DIP (COG1) I think about DIP a lot when I'm using SMARTAIL (COG2) Using PIKKPACK stimulates my interest to learn more about DIP (COG3)
Affective engagement (Hollebeek et al., 2011)	Using PIKKPACK makes me happy (AFF1) I feel good when I use PIKKPACK (AFF2) I'm proud to use PIKKPACK (AFF3) I feel very positive when I use PIKKPACK (AFF4)
Behavioral engagement (Hollebeek et al., 2011)	Shopping at PIKKPACK makes me continue using DIP (BE1) Shopping at PIKKPACK makes me recommend the DIP to other people (BE2)
Autonomy (Leung and Matanda, 2013; Halvari et al., (2010)	I feel that the way I complete my shopping at PIKKPACK is an expression of myself (A1) I feel good when I can make choices when checking out after shopping at PIKKPACK (A2) I feel that I can make choices in the way I do my shopping at PIKKPACK (A3)
Competence (Leung and Matanda, 2013 Meuter et al., (2005)	I am fully capable of using PIKKPACK (C1) I am confident in my ability to use PIKKPACK (C2) My experience increases my confidence in successfully using PIKKPACK (C3)
Relatedness (Sweeney et al., 2014)	I feel connected with other people who are using PIKKPACK (R1) I share a common bond with other people who are using PIKKPACK (R2) I feel a sense of camaraderie with other people who are using PIKKPACK (R3)
Subjective well-being (Su et al., (2016)	In general, I consider myself a very happy person (SWB1) Compared to most of my peers, I consider myself happier (SWB2) I am generally very happy and enjoy life (SWB3)

approval rate on MTurk of 95% or higher (Aguinis et al., 2021; Goodman & Paolacci, 2017). Section 1 of the questionnaire advised respondents to read a text scenario that ensured respondents' adequate understanding of PIKKPACK implementing DIPs. Section 2 contained a series of demographic questions, followed by a set of questions about antecedents and consequences of DIP-enabled customer engagement in section 3. The survey was administered to respondents who have had shopping experience at online retail stores and/or shopping using apps within last six months. A total of 355 respondents agreed to participate in the survey. After excluding 30 incomplete data entries, the final sample contained 325 usable responses, thus complying with the Hair et al., (2017) minimum sample size requirement for running partial-least squares-based path modelling.

4.3. Measures

To operationalise DIP-enabled CE and its antecedents & consequences, we adapted relevant measurement scales from the literature. Using a deductive approach (Newman, 2000), all measures were either adopted directly or were slightly adapted to ensure their relevance to our research context. For instance, customer engagement (cognitive, affective and behavioral) was measured using the adapted scale proposed by Hollebeek et al., 2011. Customer motivation to engage with DIP (autonomy, competence and relatedness) was captured using adapted items suggested by Leung and Matanda (2013), Halvari et al., (2010), Sweeney et al., (2014) and Meuter et al., (2005) respectively; and SWB was measured using the scale proposed by Su et al. (2016). Table 1 highlights all the measurement items used to test the conceptual model.

5. Data analysis

5.1. PLS structural equation modelling (PLS-SEM)

PLS structural equation modelling (PLS-SEM) using SmartPLS 3.0 (Ringle et al., 2014) in this study. PLS-SEM was used because it enables complex predictive models with small sample sizes (Hair et al., 2012); the goal in this study was to predict the key target variable (i.e., subjective well-being) and the objective is to use latent variable scores in subsequent data analysis (Sarstedt et al., 2021); PLS-SEM has greater statistical power compared to the covariance-based structural equation modelling (Sarstedt et al., 2017) and it is suitable for prediction purposes and maintaining interpretability (Henseler, 2018). A two-stage approach was used to analyze the data (Becker et al., 2012): (a) testing the measurement properties of the constructs, and (b) testing the proposed hypotheses in the structural model (Sarstedt et al., 2022).

5.2. Artificial neural Network (ANN)

The multi-analytic technique of combining SEM with ANN has gained traction in research in recent times (Sharma, 2019; Talukder et al., 2020). Haykin (2009) defined ANN as "*a massively parallel distributed processor made up of simple processing units, having a neural propensity for storing experimental knowledge and making it available for use*" (p. 2). ANN can capture non-linear relationships but can appear to use a 'black box' approach as the analysis creates hidden layers between the input and the output neurons (Leong et al., 2020). Because these hidden layers are created automatically, the ANN approach does not lend itself to hypothesis testing (Priyadarshinee et al., 2017). To overcome this limitation, researchers adopt a two-stage SEM-ANN approach (i.e., combining ANN with SEM) where in the first stage, SEM is used to test hypothesised relationships that are linear and ANN is used, in the second stage, to understand non-linear relationships (Hew et al., 2018; Xiong et al., 2022). Finally, the results from the ANN approach are compared to the results obtained from the SEM approach to determine the relative importance of the predictor constructs (Wang et al., 2022).

ANN approach does not require any distribution assumption, such as normality, linearity or homoscedasticity to be met (Liébana-Cabanillas et al., 2018; Wang et al., 2022; Xiong et al., 2022) and provides higher prediction accuracy compared to traditional techniques such as multiple linear regression (Leong et al., 2020; Lo et al., 2022).

The current study used the feed-forward-back-propagation (FFBP) multilayer perceptron (MLP) technique for the ANN analysis which is considered suitable for business research (Leong et al., 2020). This method is suitable for business research because it mirrors the complexity of human decision making where the business decision makers continually adjust the resource inputs to obtain optimal level of outputs. Feed-forward-back-propagation (FFBP) technique captures this because it continuously adjusts the weights of the input neurons in the hidden layers to obtain the output layer (Leong et al., 2020). The hidden and the output layers are automatically generated by SPSS 26.0 version and activated by the sigmoid functions (Leong et al., 2020; Liébana-Cabanillas et al., 2018). The ANN analysis employs a 10-fold cross-validation technique to manage the over-fitting problems. Furthermore, the sample of the current dataset was split into 90% training and 10% testing dataset to assess the accuracy of the ANN analysis results (Leong et al., 2020; Roy et al., 2017).

6. Results

6.1. Common method bias (CMB)

Based on the propositions of Podsakoff et al., (2012), both procedural and statistical procedures were used to test the common method bias in this study. For procedural remedies, we guaranteed participant anonymity and requested the participants to respond as honestly as possible

Table 2
Measurement Properties.

Measurement items	Loadings	*t*-values	α	CR	AVE
Cognitive engagement					
COG1	0.84	33.86			
COG2	0.81	30.76	0.77	0.87	0.69
COG3	0.84	29.70			
Affective engagement					
AFF1	0.86	37.91			
AFF2	0.86	37.32	0.89	0.93	0.76
AFF3	0.86	45.61			
AFF4	0.89	52.16			
Behavioral engagement					
BE1	0.92	92.85			
BE2	0.89	47.01	0.79	0.90	0.83
Autonomy					
A1	0.84	35.86			
A2	0.81	30.28	0.78	0.87	0.70
A3	0.86	37.90			
Competence					
C1	0.85	41.18			
C2	0.80	26.69	0.79	0.87	0.70
C3	0.86	46.47			
Relatedness					
R1	0.85	26.08	0.70	0.75	0.55
R2	0.51	3.90			
R3	0.52	3.84			
Subjective well-being					
SWB1	0.87	48.70	0.84	0.90	0.76
SWB2	0.87	47.99			
SWB3	0.88	40.87			

Notes: α: Cronbach's alpha; CR: Composite Reliability; AVE: Average variance extracted.

as there are no right or wrong answers (MacKenzie & Podsakoff, 2012). Since Harman's one-factor test has received criticism from researchers, we used the marker variable technique to detect CMB (Hulland et al., 2018). Thus, we adopted the marker variable approach suggested by Lindell and Whitney (2001) to test for the presence of common method bias. Based on their suggestions, we used respondents' mobile phone usage intensity as the marker variable. Mobile phone usage intensity is defined as the extent of mobile phone integration into respondents' daily lives. This was measured by adapting the measurement items of mobile phone usage intensity from Valenzuela et al. (2009). The variance in the dependent variable did not increase substantially with the inclusion of the marker variable in the structural model tested in this study. We found that the average correlation between latent variables in the structural model and the marker variable is 0.045, and the average significance value was 0.65. This is greater than the threshold value of 0.05. Thus, we conclude that common method bias is not a major concern in this study.

6.2. Measurement properties

The measurement properties of the research model are shown in Table 2. The measurement items of the constructs in the research model loaded significantly onto the respective latent constructs. The respective factor loadings are all greater than 0.7 with statistically significant t-values (Henseler et al., 2015). Next, we examined the reliability and validity of the constructs in the research model. The Cronbach's alpha for all the constructs is greater than 0.72 which indicates the internal consistency of the measurement model. The composite reliability of all the constructs is again greater than the threshold value of 0.70 indicating the reliability of the constructs (Hair et al., 2012). The average variance extracted (AVE) value for all the constructs was above 0.5. It implies that on average all the constructs explained more than 50% of the variance in its items (Sarstedt & Ringle, 2021), thus supporting the

Table 3
Results of hypotheses testing.

Hypothesized paths	Path coefficients	t-values	*p*-value	LCI (2.5%)	UCI (97.5%)
Direct effects					
(H1a) Autonomy → DIP-enabled cognitive engagement	0.65	6.34	0.00***	0.44	0.82
(H1b) Relatedness → DIP-enabled cognitive engagement	−0.06	1.23	0.22 ns	−0.18	0.02
(H1c) Competence → DIP-enabled cognitive engagement	0.32	3.38	0.007*	0.14	0.49
(H2a) Autonomy → DIP-enabled affective engagement	0.68	8.37	0.00***	0.49	0.80
(H2b) Relatedness → DIP-enabled affective engagement	0.14	2.38	0.02*	0.02	0.24
(H2c) Competence → DIP-enabled affective engagement	0.14	2.07	0.001*	0.02	0.28
(H3a) Autonomy → DIP-enabled behavioral engagement	0.70	8.1	0.00***	0.50	0.83
(H3b) Relatedness → DIP-enabled behavioral engagement	0.03	0.74	0.45 ns	−0.06	0.12
(H3c) Competence → DIP-enabled behavioral engagement	0.20	2.63	0.009*	0.07	0.36
Indirect effects					
(H4a) Autonomy → DIP-enabled cognitive engagement → SWB	0.1	1.66	0.09 ns	−0.01	0.23
(H4b) Relatedness → DIP-enabled cognitive engagement → SWB	−0.01	0.97	0.33 ns	−0.03	0.01
(H4c) Competence → DIP-enabled cognitive engagement → SWB	0.04	1.52	0.13 ns	−0.004	0.11
(H5a) Autonomy → DIP-enabled affective engagement → SWB	0.31	4.29	0.00***	0.176	0.464
(H5b) Relatedness → DIP-enabled affective engagement → SWB	0.62	12.74	0.00***	0.51	0.70
(H5c) Competence → DIP-enabled affective engagement → SWB	0.06	2.15	0.03*	0.014	0.129
(H6a) Autonomy → DIP-enabled behavioral engagement → SWB	0.17	3.06	0.003*	0.05	0.28
(H6b) Relatedness →	0.009	0.702	0.483 ns	−0.011	0.04
	0.05	2.313	0.02*	0.013	0.092

(continued on next page)

Table 3 (*continued*)

Hypothesized paths	Path coefficients	*t*-values	*p*-value	LCI (2.5%)	UCI (97.5%)
DIP-enabled behavioral engagement → SWB(H6c)					
Competence → DIP-enabled behavioral engagement → SWB					

Note: * indicates $p < 0.05$; *** indicates $p < 0.001$; 'ns' indicates not significant.

model's convergent validity. Discriminant validity was established as the square root of the AVE values of constructs are greater than their correlation with other constructs in the model (Fornell & Larcker, 1981). Discriminant validity was further examined using the heterotrait-monotrait ratio (HTMT). Since the HTMT ratios of the constructs are less than 0.85 (Henseler et al., 2015) we can infer those constructs in the research model possess discriminant validity.

6.3. Structural model

Next, we tested the structural model using 5,000 bootstrapped resamples based on 325 cases. The predictive relevance of the structural model was examined by checking the R^2 values and Stone-Geisser's Q^2 values (Hair et al., 2017). Results show that the R^2 value of the ultimate dependent variable (i.e., SWB) is 0.66 which is acceptable (Hair et al., 2017). The R^2 values for other endogenous variables such as cognitive engagement ($R^2 = 0.68$), affective engagement ($R^2 = 0.74$) and behavioral engagement ($R^2 = 0.73$) are acceptable too.

Thereafter we conducted the blindfolding analysis using an omission distance of 7 to assess the predictive relevance of the structural model (Tenenhaus et al., 2005). The cross-validated redundancy (Q^2) values of the endogenous constructs in the structural model are greater than 0.3. This provides additional support to the predictive validity of the structural model (Hair et al., 2017). In addition, we used the PLSpredict algorithm to provide further support for the structural model's predictive relevance (Shmueli et al., 2019). Results show that $Q^2_{predict}$ values were greater than zero for the constructs in the structural model. This shows that the proposed structural model performs better than the most naïve benchmark of the sampled indicator means.

Results (shown in Table 3) of the path analysis show that autonomy ($\beta = 0.65, p < 0.001$) and competence ($\beta = 0.32, p < 0.05$) have positive and significant impacts on DIP-enabled cognitive engagement supporting H1a and H1c. H1b was not accepted as there was no significant impact of relatedness on cognitive engagement. Results also show that autonomy ($\beta = 0.68$, $p < 0.001$), relatedness ($\beta = 0.14$, $p < 0.05$) and competence ($\beta = 0.14$, $p < 0.05$) have significant impacts on DIP-enabled affective engagement supporting hypotheses H2a, H2b, and H2c. Results support H3a and H3c as autonomy ($\beta = 0.70$, $p < 0.001$) and competence ($\beta = 0.20, p < 0.05$) have direct and positive impacts on DIP-enabled behavioral engagement. H3b was not accepted as there was no significant impact of relatedness on DIP-enabled behavioral engagement.

Next, we tested the mediation hypotheses by using indirect effects' bias-corrected, bootstrapped confidence intervals (Preacher & Hayes, 2008; Nitzl et al., 2016). Since the indirect effects between autonomy, relatedness and competence and subjective well-being (SWB) are not significant, we conclude that DIP-enabled cognitive engagement does not act as a mediator. Thus, hypotheses H4a, H4b and H4c are rejected.

The reported indirect effect between autonomy and SWB ($\beta_{indirect} = 0.31$, $p < 0.001$; LCI = 0.176, UCI = 0.464) is significant and the confidence intervals exclude zero. This shows that DIP-enabled affective engagement mediates the relationship between autonomy and SWB, supporting H5a. Similarly, the indirect effect between competence and SWB ($\beta_{indirect} = 0.06$, $p < 0.05$; LCI = 0.014, UCI = 0.127) and the indirect effects between relatedness and SWB ($\beta_{indirect} = 0.06$, $p < 0.05$; LCI = 0.014, UCI = 0.129) are also significant. In addition, since the confidence intervals do not include zero, we accept hypotheses H5b and H5c.

The reported indirect effects between autonomy and SWB ($\beta_{indirect} = 0.17$, $p < 0.05$; LCI = 0.056, UCI = 0.277) and between competence and SWB ($\beta_{indirect} = 0.05$, $p < 0.05$; LCI = 0.013, UCI = 0.092) are significant and the confidence intervals exclude zero. Thus, hypotheses H6a and H6c are supported, and DIP-enabled behavioral engagement mediates the relationship between autonomy, competence and SWB. Since the indirect effect between relatedness and SWB is not significant we conclude that the hypothesis that DIP-enabled behavioral engagement

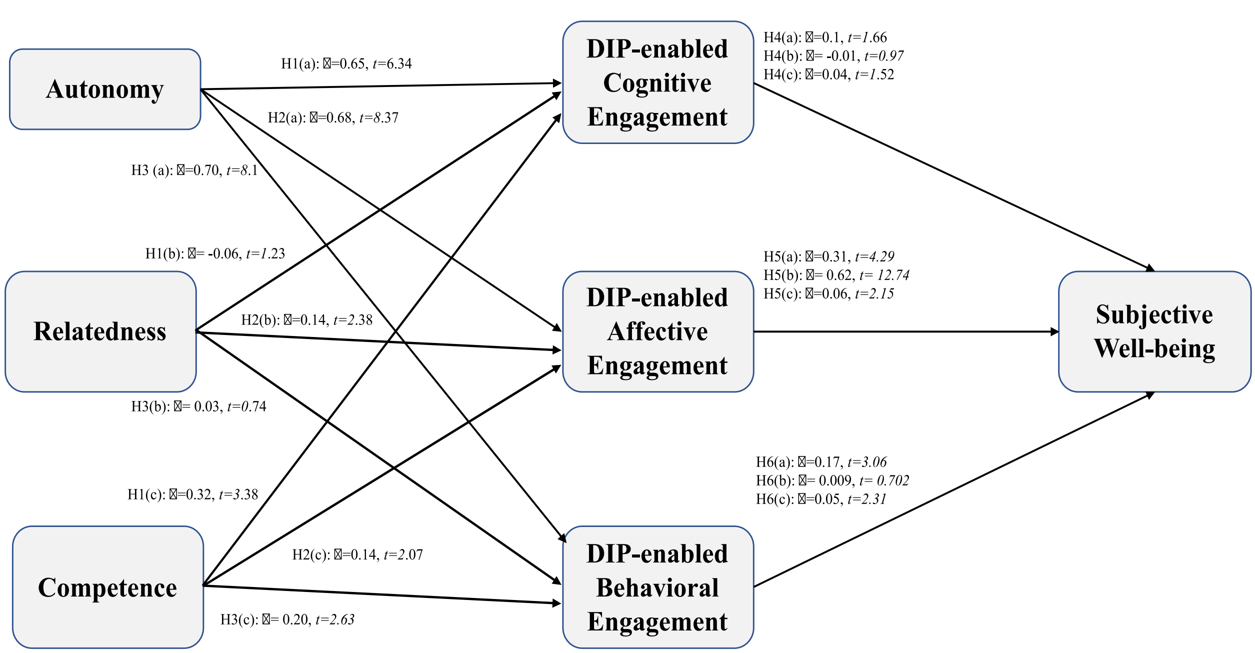

Fig. 2. Results.

Table B1
RMSE values of ANN models.

Neural Network	Model A ($R^2 = 56.99\%$)				Model B ($R^2 = 56.64\%$)				Model C ($R^2 = 58.21\%$)				Model D ($R^2 = 55.18\%$)			
	Training		Testing		Training		Testing		Training		Testing		Training		Testing	
	RMSE	SSE	RMSE	SSE	RMSE	SSE	RMSE	SSE	RMSE	SSE	RMSE	SSE	RMSE	SSE	RMSE	SSE
ANN1	0.065	1.126	0.067	0.149	0.067	1.172	0.065	0.140	0.067	1.191	0.068	0.153	0.073	1.422	0.093	0.269
ANN2	0.064	1.122	0.048	0.061	0.074	1.495	0.066	0.117	0.064	1.092	0.057	0.087	0.077	1.572	0.062	0.139
ANN3	0.070	1.311	0.102	0.282	0.060	0.984	0.072	0.140	0.063	1.066	0.060	0.098	0.074	1.454	0.074	0.179
ANN4	0.064	1.073	0.056	0.099	0.066	1.139	0.051	0.082	0.067	1.180	0.058	0.106	0.084	1.814	0.057	0.137
ANN5	0.059	0.882	0.063	0.159	0.064	1.062	0.082	0.267	0.057	0.828	0.079	0.249	0.076	1.580	0.051	0.068
ANN6	0.056	0.842	0.080	0.194	0.063	1.049	0.073	0.162	0.059	0.945	0.078	0.181	0.077	1.589	0.067	0.148
ANN7	0.067	1.151	0.100	0.379	0.067	1.153	0.090	0.305	0.071	1.321	0.099	0.371	0.075	1.484	0.051	0.094
ANN8	0.064	1.101	0.057	0.095	0.075	1.511	0.072	0.150	0.087	2.044	0.065	0.122	0.081	1.816	0.070	0.107
ANN9	0.060	0.961	0.048	0.077	0.063	1.045	0.070	0.164	0.054	0.774	0.083	0.226	0.081	1.732	0.055	0.107
ANN10	0.075	1.504	0.043	0.050	0.066	1.186	0.040	0.044	0.079	1.680	0.058	0.09	0.072	1.373	0.084	0.235
Mean	**0.064**	**1.107**	**0.066**	**0.155**	**0.066**	**1.180**	**0.068**	**0.157**	**0.067**	**1.212**	**0.070**	**0.168**	**0.077**	**1.584**	**0.066**	**0.148**
SD	**0.005**	**0.186**	**0.020**	**0.100**	**0.005**	**0.173**	**0.013**	**0.074**	**0.010**	**0.370**	**0.013**	**0.087**	**0.004**	**0.150**	**0.013**	**0.060**

Notes:
1. Model A: Input neurons are autonomy and competence while output neuron is DIP-enabled cognitive engagement.
2. Model B: Input neurons are autonomy, competence and relatedness while output neuron is DIP-enabled affective engagement.
3. Model C: Input neurons are autonomy and competence while output neuron is DIP-enabled behavioral engagement.
4. Model D: Input neurons are DIP-enabled affective engagement and DIP-enabled behavioral engagement while output neuron is subjective well-being.
5. $R^2 = 1 - RMSE/S^2$, where S^2 is the variance of the desired output according to the average SSE for the testing data.

mediates their relationship (H6b) is not supported. Fig. 2 shows results of hypotheses testing.

6.4. ANN analysis

As presented earlier, PLS-SEM analysis confirmed that all the path relationships were statistically significant except for three hypothesised relationships. These were DIP-enabled cognitive engagement to SWB, relatedness to DIP-enabled cognitive engagement and relatedness to DIP-enabled behavioral engagement. Accordingly, these non-significant relationships were not used in the ANN analysis (Hew et al., 2018; Xiong et al., 2022). Next, four ANN models were created based only on the significant hypothesised relationships from the PLS-SEM analysis. The results from the ANN analysis are provided in Appendix B and the ANN models are illustrated in Figs. B.1 to B.4 (see Appendix B). As shown in Table B.1, the Root Mean Square of Error (RMSE) for the four ANN models ranged from 0.064 to 0.077 indicating high predictive accuracy in the ANN analysis (Leong et al., 2020; Lo et al., 2022).

Next, sensitivity analysis was performed to calculate the normalised importance of the input variables and rank these in terms of their predicting capability on the output variable (Lo et al., 2022; Ng et al., 2022). The normalised importance score is the ratio of the relative importance of each input variable by the input variable having the largest relative importance (Talukder et al., 2020; Wang et al., 2022). The results from Table B.2 demonstrate that in Model A, autonomy is the most important variable in predicting DIP-enabled cognitive engagement (100% normalised importance) followed by competence (75.316%). In Model B, autonomy is the most important variable (100%) followed by competence (36.357%) and relatedness (33.186%) in predicting DIP-enabled affective engagement. Autonomy is also the strongest predictor (100%) in predicting DIP-enabled behavioral engagement followed by competence (42.349%) in Model C. Finally, Model D demonstrates that when predicting SWB, DIP-enabled affective engagement has the highest influence (100%) followed by DIP-enabled behavioral engagement (71.321%). In addition, R-square values were calculated for each of the ANN models to determine the percentage of variance explained (Leong et al., 2020; Xiong et al., 2022). As shown in Table B.2, the input variables can explain 56.99% of the variance in DIP-enabled cognitive engagement (Model A), 56.64% of the variance in DIP-enabled affective engagement (Model B), 58.21% of the variance in DIP-enabled behavioral engagement (Model C) and 55.18% of the variance in SWB (Model D).

To determine if the results obtained from ANN analysis are consistent with results obtained from PLS-SEM, the normalised importance results from the ANN analysis were compared with the path coefficient results obtained from PLS-SEM (Lo et al., 2022; Ng et al., 2022). Table B.3 shows that the results from the ANN analysis support the findings of the PLS-SEM obtained relationships. Specifically, the relative importance magnitude of the path coefficients obtained from the PLS-SEM analysis and the ANN normalised relative importance matches. For example, in Model A, the path relationship from autonomy to DIP-enabled cognitive engagement (path coefficient of 0.646) is the most important, compared to the relationship from competence to DIP-enabled cognitive engagement (path coefficient of 0.315) according to PLS-SEM results. The same finding is obtained from the ANN normalised relative importance percentage (100% normalised relative importance percentage for the relationship from autonomy to DIP-enabled cognitive engagement compared to 75.316% normalised relative importance percentage for the relationship from competence to DIP-enabled cognitive engagement). Further comparison between PLS path coefficients and ANN normalised relative importance percentage in Table B.3 for other relationships show similar matches.

Table B2
Sensitivity Analysis.

Sensitivity analysis	Model A		Model B			Model C		Model D	
	Output: Cog_Eng		Output: Aff_Eng			Output: Beh_Eng		Output: SWB	
Neural Network	**Auto**	**Comp**	**Auto**	**Comp**	**Rel**	**Auto**	**Comp**	**Aff_Eng**	**Beh_Eng**
ANN1	0.508	0.492	0.651	0.237	0.112	0.682	0.318	0.642	0.358
ANN2	0.556	0.444	0.437	0.301	0.262	0.768	0.232	0.533	0.467
ANN3	0.558	0.442	0.647	0.195	0.158	0.765	0.235	0.638	0.362
ANN4	0.503	0.497	0.627	0.205	0.168	0.708	0.292	0.505	0.495
ANN5	0.667	0.333	0.578	0.172	0.250	0.788	0.212	0.598	0.402
ANN6	0.662	0.338	0.617	0.202	0.180	0.749	0.251	0.524	0.476
ANN7	0.580	0.420	0.579	0.207	0.213	0.690	0.310	0.618	0.382
ANN8	0.544	0.456	0.456	0.255	0.289	0.526	0.474	0.505	0.495
ANN9	0.673	0.327	0.642	0.198	0.160	0.774	0.226	0.565	0.435
ANN10	0.453	0.547	0.663	0.172	0.165	0.575	0.425	0.709	0.291
Average relative importance	**0.570**	**0.430**	**0.590**	**0.214**	**0.196**	**0.703**	**0.298**	**0.584**	**0.416**
Normalized relative importance (%)	**100.000%**	**75.316%**	**100.000%**	**36.357%**	**33.186%**	**100.000%**	**42.349%**	**100.000%**	**71.321%**

Table B3
PLS-SEM and ANN results in comparison.

Path relationships	PLS path coefficient	ANN normalised relative importance (%)	Ranking based on PLS path coefficient	Ranking based on ANN normalised relative importance (%)	Comment
		Model A			
Autonomy -> DIP-enabled cognitive_Eng	0.646	100.000%	1	1	Matched
Competence -> DIP-enabled cognitive_Eng	0.315	75.316%	2	2	Matched
		Model B			
Autonomy -> DIP-enabled affective_Eng	0.677	100.000%	1	1	Matched
Competence -> DIP-enabled affective_Eng	0.138	36.357%	2	2	Matched
Relatedness -> DIP-enabled affective_Eng	0.134	33.186%	3	3	Matched
		Model C			
Autonomy -> DIP-enabled behavioral_Eng	0.701	100.000%	1	1	Matched
Competence -> DIP-enabled behavioral_Eng	0.195	42.349%	2	2	Matched
		Model D			
DIP-enabled affective_Eng -> SWB	0.464	100.000%	1	1	Matched
DIP-enabled behavioral_Eng -> SWB	0.243	71.321%	2	2	Matched

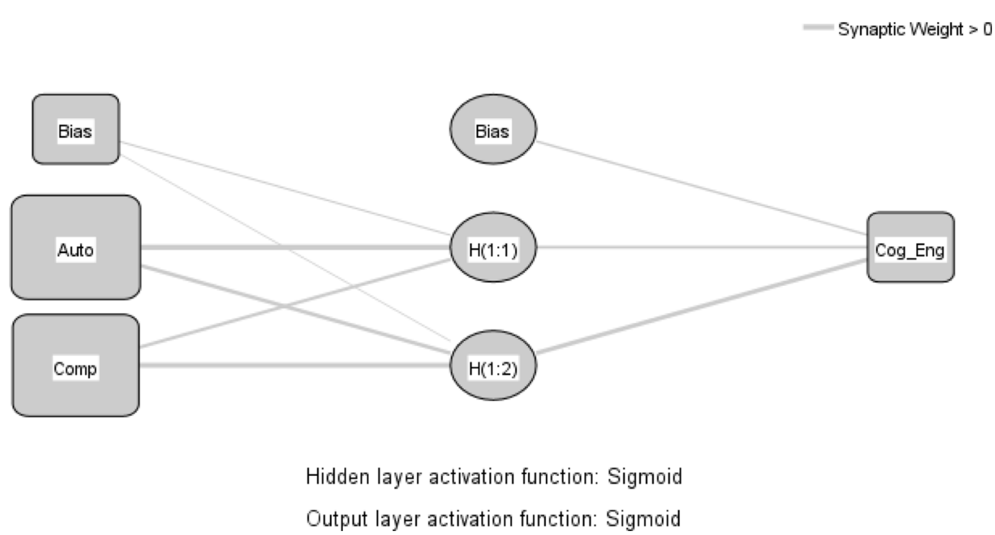

Fig. B1. ANN Model A.

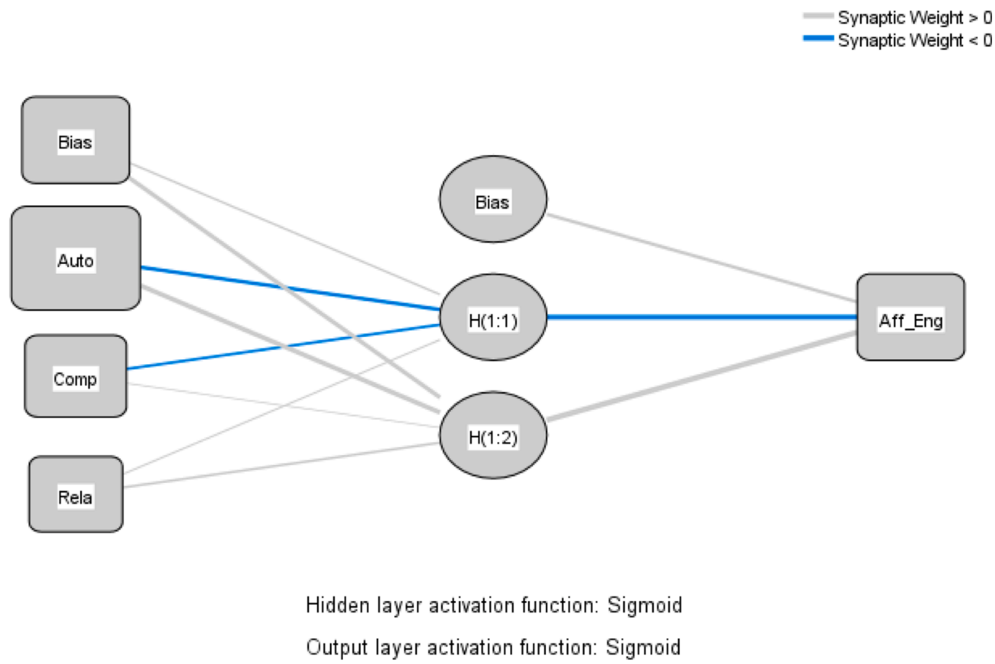

Fig. B2. ANN Model B.

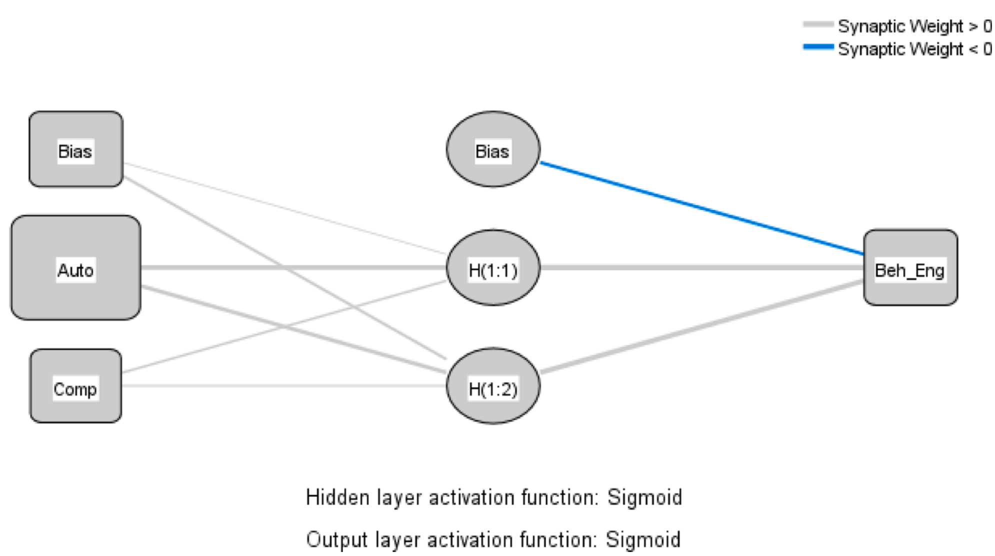

Fig. B3. ANN Model C.

7. Discussion and implications

7.1. Theoretical implications

The goal of this study was to examine (a) the antecedents and consequences of DIP-enabled customer engagement, and (b) the mediating role of DIP-enabled customer engagement in linking the antecedents to the consequences. We tested the above relationships by integrating S-DL and SDT as our theoretical framework. Our findings can be grouped into the following conclusions.

The findings from both the PLS-SEM and the ANN analysis supported the hypothesised relationships for autonomy influencing all the dimensions of CE. These results can be explained by the idea that the DIPs provide greater perceived autonomy or choice to the users leading them to be cognitively engaged with the DIPs. Previous studies have shown that greater perceived autonomy can lead users to believe in the perceived usefulness of the object (Tsai et al., 2021, Sweeney et al., 2014) leading them to be cognitively involved. Moreover, the influence of autonomy on all the dimensions of CE is greater than the influence of competence and relatedness. This suggests that the CE with DIPs is largely driven by the fact that the users prefer the independence, freedom and choices available when using the DIPs.

Competence was found to have significant relationships with all the dimensions of CE according to the PLS-SEM and ANN analysis. Competency refers to the users' ability to achieve specific goals using their capacity (i.e., operant resource). As evident from the findings, users believe that they possess higher competence when it comes to using the DIPs which results in the continual use of the DIPs leading to greater CE. This is not surprising, because the respondents were recruited from M−Turk who generally would perceive that they have higher competency in using digital platforms.

Relatedness refers to the idea that users will feel connected or

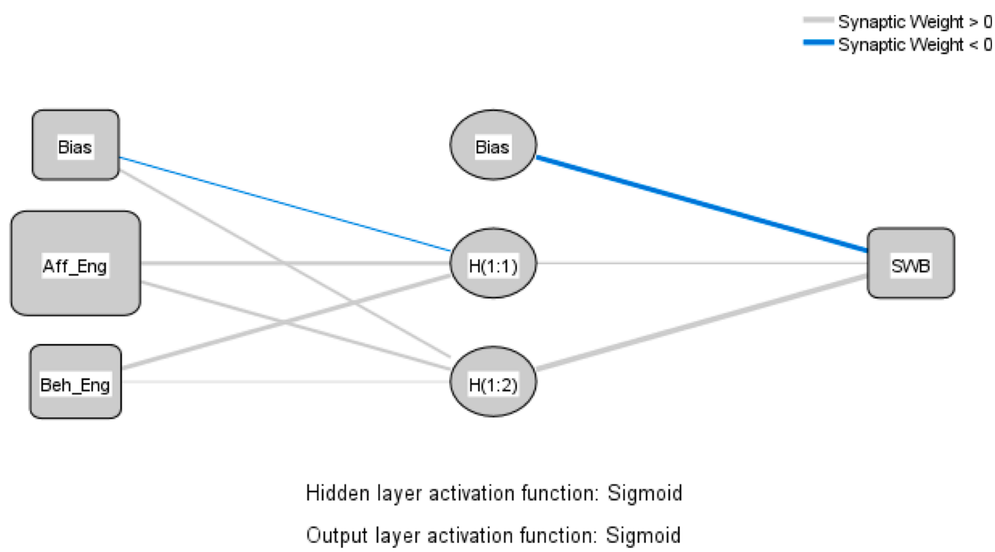

Fig. B4. ANN Model D.

belongingness with other users. This is important when users need support from other users in the form of a community (Chui, 2022). This may not be the case in the DIPs context since users do not interact with other users. This could explain the non-significant relationships between relatedness and cognitive and DIP-enabled behavioral engagement. However, the relationship between relatedness and DIP-enabled affective engagement was found to be significant. This may be because the users like using the DIPs resulting in positive emotions toward the DIPs.

In the context of this research, it was found that SWB is not influenced by DIP-enabled cognitive engagement but is influenced by DIP-enabled affective and DIP-enabled behavioral engagements. This is in line with Kim et al., (2014) assertion that individuals' SWB is influenced more by affective responses compared to rational responses. SWB is a psychological concept which measures individuals' cognitive judgements of overall life satisfaction and affective judgements of emotion. Therefore, it is likely that the use of DIPs makes the users feel happy about themselves which translates into greater SWB. This could be because the DIPs are easy to use, making the users feel less stressed and as a result, they do not have to spend cognitive effort (i.e., to think about) using the DIPs. This is also evident from the results that show that DIP-enabled cognitive engagement does not mediate any relationships from ARC to SWB.

We also find that DIP-enabled affective engagement mediates the relationship between ARC and SWB. This suggests that when the use of DIPs influences the emotional aspects (i.e., affect) of the users, they are more likely to develop a position perception of their life satisfaction and overall emotion. As noted earlier in this section, affective engagement with the DIPs is more likely when users perceive that they have fulfilled the ARC aspects of needs satisfaction when using the DIPs.

The results show that DIP-enabled behavioral engagement mediates the relationship between autonomy and competence and SWB but does mediate the relationship between relatedness and SWB. This result can be explained by the fact that the users were not able to see other users (i.e., lack of relatedness) during their interaction with DIPs. Therefore, the users mostly focus on their perceptions of autonomy and competency when using the DIPs. In other words, the more autonomy (i.e., freedom) and competency (i.e., capability) the users perceive they possess when using the DIPs, the more likely they are to engage behaviorally (e.g., by spending energy, time and effort) with the DIPs which in turn make them emotionally satisfied and happy (i.e., increase their sense of SWB).

Lastly, we used SEM-ANN approach, which is relatively new to the customer engagement and the DIP literature, and unpacks the nonlinear association between human psychological needs, customer engagement and subjective well-being. With the use of ANN analysis, we were able to determine normalised importance of the input variables and rank these based on their predictive capability on the output variable. This approach contrasts with the existing studies that compute beta coefficients of the SEM analysis. Our analysis in this context is somewhat of a paradigm shift, where researchers not only focus on testing linear causal relationships but can also focus on the nonlinear associations between predictors and dependent variables.

Overall, the study contributes to the literature by shedding light on the complex relationships between human psychological needs, customer engagement and subjective well-being, in the context of DIP, and through the integrated theoretical lenses of service-dominant logic and self-determination theory. The results explain that the direct relationship between human psychological needs satisfaction (autonomy, relatedness and competence) and subjective well-being is mediated by customer engagement (cognitive, affective and behavioral). Specifically, findings show that autonomy and competence have significant relationships with all the dimensions of customer engagement (cognitive, affective and behavioral). Subjective well-being, though, is not influenced by cognitive engagement, but is influenced by affective and behavioral engagement.

7.2. Managerial implications

Understanding the enablers and consequences of DIP-enabled CE is integral to re-conceptualizing retailers' offerings as DIPs. This is specifically essential in the era of experience-driven service interactions where positive experiences are critical in deriving value for both customers and firms. CE has been cited as the source of competitive advantage (Kumar & Pansari, 2016). Hence, by recognizing how this practice could be motivated, service providers can strengthen their interactions in the technological environments and enable positive brand consequences.

First, our findings show that autonomy influences all the dimensions of CE. Based on this finding, managers are advised to provide actions or steps which increase the perception of autonomy among users of DIPs. For example, the users can be allowed to choose and design their own shoes/products using the DIPs. This will consequently increase engagement with the DIPs and increase SWB. However, designers should also be careful to not make the DIPs too complicated to operate, as this may adversely impact the perceived competency among the users leading to lower CE.

Previous studies have shown that relatedness positively influences behavior (Sweeney et al., 2014) and engagement (Chiu, 2022). In contrast, our findings suggest that relatedness impacts only the affective engagement. This implies that the DIPs should be designed to make them feel relatable to the users which leads to affective engagement. For example, companies can design the DIPs by providing instant feedbacks to the users about their use of DIPs. This will likely create positive feelings among the users and increase CE.

In the current study, relatedness was not found to impact cognitive and behavioral engagement which could be because of scenario lacked information on how the users may connect with other users of the DIPs. Chiu (2022) noted that relatedness becomes important when support from other users is needed because of uncertain and unfamiliar situation. Therefore, companies should allow the users to interact with each other (i.e., receiving and giving feedback from other users) when using the DIPs. This will likely increase CE because of greater relatedness.

The results also show that DIP-enabled affective engagement mediates relationships between ARC and SWB. Technologies have been shown to create feelings of SWB in several contexts (Kim et al., 2020). This implies that DIPs should be designed to promote the feelings of escapism, entertainment, challenge, fantasy, and pleasure which have been shown influence psychological well-being (Li et al., 2014, Singh et al., 2017). For example, the DIPs can be designed to make these entertaining by utilising vivid sound and video.

Similarly, the DIPs should be easier to use or operate as the results show that the influence on SWB by autonomy and competence are mediated by DIP-enabled affective engagement. This implies that when the users do not feel constraint or face difficulty in using the DIPs, they are more likely to be engrossed in using the DIPs leading them to perceive higher SWB.

8. Limitations and future research directions

Several limitations of this study reflect avenues for further research. First, in our study, we identified one driver of DIP-enabled CE, namely customer motivation (autonomy, relatedness, and competence). CE with DIP may not only be triggered solely by their motivation but could also be driven by trust, and commitment (Pansari & Kumar, 2017, de Oliveira Santini et al., 2021). Future research can extend the model to include additional factors that capture the drive CE, such as those proposed by Islam et al., (2019) and Lim and Rasul (2022) including several brand-based, customer-based, industry-based, and marketer-based platform-based factors. Secondly, while this paper integrates the theoretical underpinnings of S-D logic and the SDT, future research may consider integrating other and/or complementary theoretical lenses into its investigation, including social exchange (Hollebeek, 2011), resource-based view (Hollebeek, 2019) relationship marketing theory (Vivek et al., 2014), service logic (Grönroos, 2008), regulatory engagement theory (Higgins, 2006; Higgins & Scholer, 2009), engagement theory (Pansari & Kumar, 2017) and others to accomplish further theoretical understanding of DIP enabled CE (MacInnis, 2011). Third, future research could contrast and validate the model's relationships across other types of DIPs with different characteristics, such as search and advertising platforms, content platforms, social media platforms, and other service platforms focused on, for example, crowdsourcing or crowdfunding (Rangaswamy et al., 2020). Fourth, extant research also highlights that customer well-being can operate as an antecedent of CE (e.g., Horwood & Anglim, 2019). Future research could also investigate the reciprocal relationships between well-being and DIP-enabled customer engagement. Nevertheless, a text scenario-based study has its limitations in terms of gaining insight into well-being through the lens of customer need satisfaction. Therefore, future research could use other research methods – such as field studies and field experiments – and take different well-being aspects – like self-efficacy and technology anxiety– into consideration (Henkens et al., 2021). Finally, the empirical study examined one organisation (PIKKPACK) through the conceptualisation of DIP as APPI with respondents from one country (i.e., Australia). As such, future research can explore the conditions under which DIP-enabled CE emerges in other settings and/or countries.

CRediT authorship contribution statement

Sanjit K. Roy: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Gaganpreet Singh:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Saalem Sadeque:** Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation. **Paul Harrigan:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Kristof Coussement:** Writing – review & editing, Supervision, Methodology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Imagine you would like to buy a new pair of customized shoes for yourself. You come across a service PIKKPACK that offers access to different shoe items using the digitalized interactive platform (DIP). The DIP of PIKKPACK offers you the autonomy to edit and design customised shoes that are otherwise not available in the regular market. The possibility of selecting between shoe colour and sole material along with different types of sole colour and shoelace colour would result in multiple shoe permutations. The PIKKPACK's DIP also offers relevant product information, including its use in different climatic conditions, country of origin, and how to wash the product. The standard PIKKPACK kit shipped to you will consist of all unassembled shoe items an instructions kit and a tutorial on how to assemble the shoes yourself. Upon assembling, you can use the product. In this way, you have control over creating your shoemaking and usage experience. The engagement generated will be contingent on the autonomy, competence and relatedness offered by the PIKKPACK'S DIP. PIKKPACK also maintains an appointment-based showroom for its users to physically create, engage and experience the product. Overall, positive engagement is likely to give you higher satisfaction and eventually influence your well-being (and vice versa).

Appendix B

See Tables B.1, B.2, B.3 and Figs. B.1 to B.4

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