



Cognitive Influences in Second-Hand Markets: From Perception to Purchase in Rural Smartphone Consumption

Journal:	<i>Journal of Enterprising Communities: People and Places in the Global Economy</i>
Manuscript ID	JEC-03-2025-0069.R1
Manuscript Type:	Academic Papers
Keywords:	Circular economy, Cognition, Community, Decision making

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Abstract

Purpose

This study examines how rural consumers make second-hand purchase decisions beyond economic necessity. Using schema theory, we explore how perceived price fairness, product features, product quality, and sustainable community influence drive purchase intentions in the rural second-hand smartphone market.

Design/Methodology/Approach

We surveyed 225 rural New Zealand second-hand smartphone users and tested our hypotheses using Partial Least Squares - Structural Equation Modelling to analyze key factors influencing purchase intentions.

Findings

This study challenges the assumption that rural consumers evaluate second-hand goods solely on objective attributes, showing that decision-making is shaped by past experiences, social influences, and perceived price fairness. Rather than a purely economic assessment, price fairness integrates product quality and features, influencing consumer engagement. Additionally, community norms and sustainability messaging shape purchasing decisions, emphasizing social influences over rational education.

Practical Implications

Businesses and policymakers must move beyond price incentives and leverage social networks and sustainability messaging to shape consumer schemas. Trust in second-hand markets depends on perceived fairness, quality, and social validation, highlighting the importance of community-driven interventions over traditional rational education efforts.

Originality/Value

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3 This study (1) extends schema theory by demonstrating how rural consumers use cognitive
4 shortcuts and social learning to navigate information asymmetry, (2) reframes perceived price
5 fairness as a cognitive framework rather than a transactional factor, and (3) highlights
6 sustainability as a dynamic consumer heuristic.
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15 **Keywords:** Price Fairness, Product Features, Product Quality, Sustainable Community
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Introduction

Second-hand consumption is undergoing a cognitive transformation, driven by shifting consumer priorities and changing perceptions of value (Gilal et al., 2024). Nowhere is this shift more evident than in the global rise of refurbished electronics, a market projected to grow from USD 55.6 billion in 2022 to nearly USD 120 billion by 2026 (Statista, 2024). Yet, while existing research often centres on economic or hedonic motives among urban consumers, rural markets remain underexplored, despite their distinct consumption patterns and decision-making structures (Lewis & Rauturier, 2019; Gilal et al., 2024).

This gap is particularly relevant as second-hand products become intertwined with digital inclusion, sustainability, and resource-conscious living. Prior studies (Fan, 2021; Zufall et al., 2020; Hvass, 2022) have called for deeper analysis into second-hand product adoption across technology sectors, including smartphones, laptops, and household appliances. However, much of this work generalises across geographies and omits the socio-cognitive realities of rural consumers, who must navigate information asymmetry, social pressures, and environmental concerns simultaneously.

New Zealand presents an ideal setting for this inquiry. With 60–85% of the population engaging in second-hand consumption (Statista, 2024), the country offers a unique blend of high sustainability awareness, digital adoption, and rural community cohesion. In these settings, consumer decisions extend beyond affordability to reflect values of trust, thrift, and environmental stewardship. These motivations are particularly salient in rural New Zealand, where access to diverse markets is limited and community endorsement plays a key role in consumer behaviour (Whitehead et al., 2022; Elers et al., 2022).

Thus, this study asks: How do rural consumers make second-hand purchase decisions, and what factors influence their decision-making processes beyond economic necessity? This question is particularly crucial given insights from Mukherjee et al. (2020) that in rural settings,

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3 many second-hand shoppers are driven not just by financial constraints but also by a desire to
4 make savvy purchasing decisions, reduce financial strain and environmental impact, and
5 embrace a minimalist or anti-consumption ethos.
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10 Drawing from schema theory (Lee and Kim, 2024), we argue that rural second-hand
11 consumption is governed by socially reinforced cognitive shortcuts (schemas) that help
12 consumers evaluate product quality, features, and price fairness in the face of uncertainty and
13 limited information. This perspective suggests that rural individuals may adopt distinct
14 purchasing behaviors influenced by varying access to information, technological infrastructure,
15 and cultural norms regarding used items, diverging from those observed in urban contexts
16 (Liang and Xu, 2018, Arunachalam et al., 2020). For instance, rural consumers may rely
17 heavily on cognitive shortcuts like availability bias and social proof when assessing the
18 physical quality of refurbished smartphones (Zhang et al., 2024). These decision patterns
19 mirror findings in technology acceptance research, where social influence, effort expectancy,
20 and facilitating conditions shape behavioural intention in underserved environments
21 (Venkatesh et al., 2012). Limited exposure to newer models and technological advancements
22 could constrain their perceptions of the features offered by second-hand options. Furthermore,
23 the tight-knit nature of rural communities likely amplifies social influences on cognitive
24 processes, fostering collective decision-making and shared knowledge (Vakulenko et al.,
25 2022). This interaction with their existing schemas potentially influences how they perceive
26 and evaluate second-hand goods in ways that differ from urban consumers (White et al., 2019).
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49 Moreover, the growing awareness of electronic waste and its environmental impact is
50 reshaping consumer preferences towards more sustainable options, as consumers integrate
51 environmental considerations into their cognitive frameworks (Singh et al., 2022). The
52 purchase of second-hand smartphones is seen not only as economically advantageous but also
53 as an environmentally conscious choice, reducing the demand for new production and the
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3 associated ecological footprint (Ek Styvén and Mariani, 2020, Gilal et al., 2024). This
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5 behavioral shift, driven by a rising environmental ethos, leads consumers to mitigate the effects
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7 of electronic waste, thus fueling the second-hand device market (Islam et al., 2021).
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10 Building on prior research into the implications of second-hand products (White et al.,
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12 2019, Mukherjee et al., 2020), our study enhances the literature by examining how perceived
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14 price fairness mediates the relationship between product features, perceived product quality,
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16 and sustainable community influence in shaping purchase intentions in the rural second-hand
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18 smartphone market. Our research makes three main contributions to the burgeoning
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20 understanding of purchase intentions in rural environments.
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24 **First, we extend schema theory by showing how rural consumers use experiential and**
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26 **social heuristics to evaluate second-hand goods, especially in contexts of limited technical**
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28 **transparency (Liang and Xu, 2018, Arunachalam et al., 2020).** Our findings highlight perceived
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30 price fairness as a cognitive anchor, not merely an economic assessment, but a mental
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32 framework integrating perceptions of product quality and emotional consistency, which
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34 influences consumer trust and long-term market engagement (Alkaabi, 2022).
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38 Moreover, we reveal that schema adaptation is not an isolated cognitive process but a
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40 socially mediated phenomenon, where community norms and sustainability messaging actively
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42 reshape consumer perceptions and behaviors (White et al., 2019, Ek Styvén and Mariani,
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44 2020). This challenges conventional interventions that rely on rational education, suggesting
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46 that leveraging social networks and contextual cues is more effective in shifting consumer
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48 attitudes toward sustainable and economically viable choices (Lee and Kim, 2024).
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52 **Third, we demonstrate that sustainable community influence, through peer endorsements**
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54 **and environmental messaging can embed sustainability as a cognitive heuristic, shaping**
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56 **purchasing decisions in ways that economic or rational appeals alone cannot (Mukherjee et al.,**
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58 **2020, Gilal et al., 2024, Emami et al., 2024).** This reconceptualization expands schema theory,
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3 emphasizing that consumer behavior in resource-limited settings is driven by an interplay of
4 trust, cognitive efficiency, and social reinforcement, with significant implications for second-
5 hand market strategies and sustainability initiatives.
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10 In doing so, this research reframes rural consumption not as a matter of deprivation, but as
11 a site of cognitive ingenuity, social learning, and sustainability leadership. It responds to recent
12 calls for more geographically and cognitively grounded models of second-hand purchasing
13 (Mukherjee et al., 2020; Hansen & Le Zotte, 2022; Gilal et al., 2024).
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19 The rest of the paper is organized as follows: it begins by exploring the theoretical
20 background, establishing the foundation for hypothesis development. Next, it details the
21 methodology and discusses the quantitative analyses. The discussion then moves to the
22 theoretical and practical implications of the findings. The paper concludes by acknowledging
23 the study's limitations and suggesting potential avenues for future research.
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33 **Theoretical framework and hypothesis development**

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35 Schema theory explains how individuals' structure and interpret information using
36 cognitive frameworks known as schemas (Lee and Kim, 2024). These schemas influence
37 perception, memory, and decision-making by shaping how individuals focus their attention,
38 encode new experiences, and retrieve information, allowing them to navigate complex
39 decisions efficiently (Pidduck et al., 2020). In the context of second-hand purchases,
40 particularly in rural markets, consumers develop schemas informed by their unique
41 socioeconomic conditions, cultural backgrounds, and lived experiences (Mukherjee et al.,
42 2020). These schemas play a decisive role in shaping perceived price fairness, perceived
43 product features, perceived product quality, and ultimately, purchase intentions.
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56 Schema theory is particularly suited for rural contexts, where decision-making is driven by
57 heuristics, social validation, and experiential learning (Pidduck et al., 2020). Compared to
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3 frameworks like the Theory of Planned Behaviour (TPB) and Signalling Theory, schema theory
4 provides a more context-sensitive lens for understanding consumer decisions in rural second-
5 hand markets. TPB assumes deliberate intention formation based on attitudes, norms, and
6 control, which may not reflect the cognitive realities of rural consumers facing information
7 constraints (Yadav and Pathak 2017). Signalling Theory centres on credible market cues (e.g.,
8 warranties), often lacking in informal rural transactions (Kirmani and Rao 2000). In contrast,
9 schema theory explains how consumers rely on internalised experience and social learning to
10 make satisficing decisions. Its ability to capture both individual cognition and socially
11 reinforced heuristics makes it well suited to trust-based, cross-cultural rural settings (Pidduck
12 et al., 2020; Lee & Kim, 2024).

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26 Rural consumers often operate under cognitive and infrastructural constraints, including
27 low digital literacy and limited device access (Nie et al., 2020), making them more reliant on
28 informal signals, such as community endorsements, word-of-mouth, and previous usage
29 experiences (Vakulenko et al., 2022; Arunachalam et al., 2020). In digitally evolving rural
30 environments, such as in New Zealand, smartphone adoption has increased significantly due
31 to infrastructure investments (MBIE, 2022), but digital literacy and comparison-shopping skills
32 remain unevenly distributed (Elers et al., 2022). This reinforces the role of cognitive shortcuts
33 (schemas) as critical decision-making tools in environments where full market transparency is
34 unavailable. Moreover, rural consumption is often framed by embedded social norms and
35 frugal mentalities, further shaping how consumers evaluate risk and value
36 (Jayawickramarathna et al., 2021).

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51 For example, rather than assessing second-hand smartphones based solely on technical
52 specifications, rural consumers may rely on community feedback, prior device use, or trust in
53 peer recommendations (Jayawickramarathna et al., 2021). These processes demonstrate
54 schema-guided evaluations, which are not only cognitive but also socially mediated.
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3 Additionally, trust in rural communities is shaped by cross-cultural and collective experiences,
4 especially within Māori and Pasifika populations, where purchasing decisions are influenced
5 by communal norms and social validation. These trust dynamics are culturally mediated; Māori
6 and Pasifika worldviews often emphasize collectivism, reciprocity, and social proof in market
7 behaviour, leading to a unique configuration of trust that is relational and community-bound
8 rather than individualistic (Barnes et al., 2024; Vakulenko et al., 2022). This distinguishes trust
9 formation in rural New Zealand from more individualist, urban, or Western models of
10 consumer behaviour, necessitating a theoretical lens sensitive to these communal
11 underpinnings.
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24 Perceived price fairness is central to second-hand purchasing decisions, as consumers
25 assess whether the cost of a refurbished product is justified given its condition, longevity, and
26 brand reputation (Makov et al., 2019). Existing schemas influence this judgment by drawing
27 on past experiences with second-hand goods and broader community norms regarding value-
28 for-money (Yang et al., 2023). Additionally, perceived product features and perceived product
29 quality are filtered through schemas that determine expectations about functionality, durability,
30 and potential trade-offs between price and performance (Mukherjee and Pandelaere, 2023). For
31 instance, in rural settings where access to repair services is limited, schemas may prioritise
32 durability and reliability over cost alone, shaping both evaluations and purchasing behaviours.
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45 Schemas are also socially constructed and reinforced through sustainable community
46 influence, where local businesses, peer networks, and social norms shape collective consumer
47 perceptions (Gilal et al., 2024). When sustainability initiatives and community-driven
48 campaigns highlight the environmental and economic benefits of second-hand consumption,
49 they contribute to schema adaptation, shifting consumer priorities beyond cost savings toward
50 broader sustainability considerations (White et al., 2019, Yang et al., 2023). As a result,
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3 evolving schemas can enhance purchase intention by positioning second-hand goods as both
4 financially and ethically advantageous choices. Figure 1 illustrates this conceptual framework.
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8 *Insert Figure 1 about here*
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10 **Hypothesis development**

11 *Perceived product quality, perceived price fairness and purchase intentions*

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13 Product quality refers to the customer's perception of a product's overall quality or superiority
14 compared to alternatives (Mukherjee and Pandelaere, 2023). According to schema theory, this
15 perception is influenced by cognitive frameworks that consumers develop through their
16 experiences and knowledge (Lee and Kim, 2024). Therefore, perceived quality is a subjective
17 evaluation rooted in individual schemas and experiences rather than an objective assessment
18 (Pidduck et al., 2020). Consumers use their schemas to evaluate quality indicators such as brand
19 name, reputation, and physical attributes. When a product aligns with the consumer's schema,
20 it reinforces positive expectations and increases confidence in the product, directly influencing
21 purchase intentions.
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36 Perceived product quality alone may not suffice to drive purchase intentions in rural
37 settings if prices are perceived as unfair (Arunachalam et al., 2020). High perceived quality
38 increases consumer interest, but if the product is priced disproportionately high, consumers
39 might feel exploited and reluctant to purchase (Mukherjee and Pandelaere, 2023). Perceived
40 price fairness bridges this gap by ensuring that the quality-price ratio meets consumer
41 expectations (Zhang et al., 2024). Moreover, perceived price fairness builds trust and reduces
42 perceived risk in rural markets (Vakulenko et al., 2022). Even if a product is perceived to be
43 of high quality, an unfair price can introduce doubts about the seller's integrity and the true
44 value of the product (Mukherjee and Pandelaere, 2023). This trust is crucial for converting
45 quality perceptions into purchasing actions, as consumers are more likely to buy from sellers,
46 they deem trustworthy (Yang et al., 2023).
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3 When a product's price aligns with consumers' schemas, such as the belief that a fair
4 price reflects good value, consumers experience cognitive consistency, which reinforces
5 satisfaction and increases the likelihood of buying the product (Liang and Xu, 2018). A fair
6 price suggests that the consumer is not being overcharged, fostering a sense of equity and
7 fairness (Makov et al., 2019). This emotional satisfaction translates into a stronger intention to
8 purchase, as consumers feel confident, they are making a wise and justified decision. Therefore,
9 we propose the following hypothesis:

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19 *H1: Perceived price fairness mediates the relationship between perceived product*
20 *quality and purchase intentions for second-hand smartphones in rural markets.*
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26 *Perceived product features, perceived price fairness and purchase intentions*

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28 Perceived product features play a crucial role in shaping consumer purchase intentions by
29 influencing both rational assessments and emotional schemas (Zhang et al., 2024). When
30 evaluating second-hand smartphones, consumers prioritize features that align with their needs,
31 preferences, and expectations (Gilal et al., 2024). Attributes such as camera quality, processing
32 speed, battery life, and storage capacity directly impact perceived utility and functionality,
33 making a second-hand smartphone with advanced camera features or ample storage at a
34 competitive price a valuable purchase (Makov et al., 2019).
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44 Moreover, product features can stimulate emotional responses. Advanced features or
45 innovative technology can evoke feelings of excitement, satisfaction, or status (Chen et al.,
46 2023). These emotional schemas strongly influence purchase decisions, as consumers seek
47 products that resonate with their aspirations and lifestyle preferences (Gilal et al., 2024).
48 Consumers use features as indicators of a product's overall performance and reliability.
49 Features that stand out for innovation, durability, or usability distinguish a smartphone from
50 competitors and enhance its perceived value (Mukherjee et al., 2020). This differentiation
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3 guides consumers toward products with unique and desirable features in competitive markets.
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5 In rural areas, the importance of perceived product features may be heightened due to limited
6 access to a wide range of products (Jashari-Mani and Zeqiri, 2024). Features such as battery
7 life and durability can be particularly crucial, given the challenges of infrastructure.
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12 Product features hold substantial sway in the pricing of second-hand smartphones
13 (Godinho Filho et al., 2024). Features such as the device's model, technological specifications,
14 camera quality, battery life, and overall condition are critical determinants of its perceived
15 value in the second-hand market (Godinho Filho et al., 2024). Consumers use their cognitive
16 schemas, formed by previous experiences and knowledge, to evaluate these features and make
17 pricing judgments (Lee and Kim, 2024). For instance, a second-hand smartphone with the latest
18 operating system, high-resolution camera, and minimal wear and tear is likely to be priced
19 higher than an older model with outdated technology and visible signs of use (Zhang et al.,
20 2024). This differential pricing reflects the perceived value these features hold for consumers,
21 shaped by their cognitive frameworks and expectations (Liang and Xu, 2018).
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36 Consumers in rural markets seek the best value for money, a device that offers maximum
37 functionality and reliability at a reduced price (Arunachalam et al., 2020). Features that
38 enhance user experience, such as a faster processor, or better connectivity options, add
39 significant value and drive purchase intentions (Makov et al., 2019). However, if the price is
40 perceived to be too high, even for a smartphone with excellent features, it might deter potential
41 buyers, especially those looking for budget-friendly options in the second-hand market (Gilal
42 et al., 2024). Therefore, we propose the following hypothesis:
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51 *H2: Perceived price fairness mediates the relationship between perceived product*
52 *features and purchase intentions of second-hand smartphones.*
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3 Sustainable community influence, *perceived price fairness and purchase intentions*.
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5 Sustainable community influence constitutes the fabric of a consumer's societal
6 environment, influencing choices and behaviours within that context (Yang et al., 2023).
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8 According to schema theory, within any given society, a tapestry of individuals presents a
9 spectrum of tastes and behaviours that shape the cognitive schemas of consumers (Pidduck et
10 al., 2020). These variances in behaviour significantly sway personal preferences, as consumers
11 frequently gravitate towards conforming to established societal norms and standards (White et
12 al., 2019).
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21 In rural settings, sustainable community influence plays a pivotal role in shaping consumer
22 purchase intentions by promoting awareness, establishing social norms, and cultivating trust in
23 sustainable practices (Vakulenko et al., 2022). Advocacy for sustainable products like second-
24 hand smartphones, through educating consumers about their environmental benefits and
25 potential for waste reduction, encourages consumers to prioritize and consider products aligned
26 with sustainability values (Armutcu et al., 2024). Trust is integral to purchase decisions in rural
27 settings where access to diverse markets and information may be limited (Arunachalam et al.,
28 2020). Endorsements from community leaders or peers enhance consumer confidence in the
29 quality and reliability of sustainable products (Godinho Filho et al., 2024). This trust minimizes
30 perceived risks associated with purchasing second-hand goods and bolsters consumer buying
31 decisions (White et al., 2019).
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46 In close-knit rural communities, peer recommendations and community opinions carry
47 significant weight. Positive feedback about the fairness of prices for second-hand smartphones
48 from social circles reinforces consumer confidence and purchase intent (Gilal et al., 2024).
49 Social validation of price fairness amplifies consumer trust in community judgments,
50 influencing their decisions positively (Alnes and Haugom, 2024). Conversely, perceived unfair
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pricing can diminish the impact of social recommendations on purchase intentions (Alkaabi, 2022).

While sustainable community influence raises awareness of the benefits of sustainable products, awareness alone may not translate into purchasing decisions if consumers perceive prices as unfair (Yang et al., 2023). Rural consumers often prioritize cost-effectiveness and utility, valuing products that offer practical benefits at reasonable prices (Vakulenko et al., 2022). Perceived price fairness reinforces the value proposition of sustainable products, aligning price with perceived quality and benefits advocated by the community (Darku and Akpan, 2020). This alignment enhances consumer perceptions of product value and encourages them to choose sustainable options that support environmental goals (Singh et al., 2022). Hence, the following hypothesis is proposed:

H3: Perceived price fairness mediates the relationship between sustainable community influence and purchase intentions of second-hand smartphones

Methods

Research setting

New Zealand provides an intriguing context for studying consumer behavior regarding second-hand products. With its strong commitment to environmental sustainability and conservation, New Zealand's interest in second-hand goods aligns with global efforts to reduce electronic waste and promote circular economy practices (Elers et al., 2022). New Zealanders, who are enthusiastic adopters of technological advancements and conscious of environmental issues, generally prioritize experiences over expensive material possessions. This cultural inclination makes second-hand products a perfect fit within the broader societal values.

In New Zealand, rural communities are seen to exist on a continuum, ranging from "very remote" areas, such as isolated farms and fishing villages, to peri-urban towns that service rural

regions (Ministry of Health, 2024). Trust within tight-knit rural communities enhances the appeal of second-hand products, as recommendations and shared values about sustainability hold significant sway (Whitehead et al., 2022). Rural consumers, who may have limited access to diverse markets and higher costs for new technology, often turn to second-hand options for their practicality and affordability. This makes rural New Zealand an ideal setting to study second-hand phone purchasing behavior, as it encapsulates the intersection of technological adoption, sustainability values, and community trust (Elers et al., 2022). Additionally, New Zealand's cultural values that promote sustainability and responsible consumption contribute to the popularity of second-hand products (Whitehead et al., 2022).

Data collection

For data collection purposes, 'rural' was defined as areas with fewer than 2,500 residents. This classification included towns such as Edgecumbe, Moerewa, Taihape, and Methven, which supported the surrounding rural areas (Statistics New Zealand, 2023). This definition was broader than Statistics New Zealand's categorisation of areas with fewer than 1,000 residents but aligned with the Ministry of Health (2024)'s depiction, showing that most of the nation was in the green category, with urban areas shaded red, pink, and orange, as illustrated in Figures 2 and 3. While concerns regarding the digital divide in rural areas are valid, recent government initiatives, such as New Zealand's Rural Broadband Initiative (RBI), have significantly expanded internet access across rural towns (MBIE, 2022). Given our target sample of second-hand smartphone users, a group inherently engaged with digital tools, recent studies have shown that trust and perceived value are shaped by online interactions and digital appraisals even in peripheral regions, the use of online panels was appropriate (Van Nguyen et al., 2025).

Participants were recruited through a geographically stratified online panel and had to meet three inclusion criteria: (1) reside in a rural area, defined as a town with fewer than 2,500

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3 people (Ministry of Health, 2024); (2) have purchased or received a second-hand smartphone
4 within the previous 24 months; and (3) be aged 18 or older. These eligibility criteria were
5 embedded as screening questions at the beginning of the survey to ensure the sample was
6 composed of consumers with recent, relevant second-hand market experience. As a result, the
7 method allowed for efficient, ethically compliant data collection among digitally active rural
8 consumers.
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21 The data were gathered using a Qualtrics survey panel, with full ethics approval
22 (Unitec:18/3270). Employing the tailored design method (Dillman et al., 2014), we crafted and
23 electronically disseminated the survey. The survey instrument was developed through an
24 extensive review of relevant literature and subsequently subjected to rigorous pre-testing
25 involving three researchers and 15 second-hand smartphone users. Adjustments were
26 iteratively made based on pre-test feedback to enhance clarity and comprehension.
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35 To mitigate response interdependence, questions pertaining to predictor, mediator, and
36 dependent variables were interspersed throughout the survey instrument. We obtained 305
37 responses in total. Adhering to the recommendations by Bernerth et al. (2021) on online
38 surveys, we excluded respondents who exhibited fast completion (12), consent rejections (3),
39 indicated they didn't use a second-hand (refurbished) phone (50), provided incomplete
40 responses (9), or failed an attention test (6). We used a simple validation question as a
41 benchmark for our attention test by asking respondents, "Please choose the color blue from the
42 options below," where the options included various colors.
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54 This process resulted in a usable sample of 225 respondents. Of these, 113 were male
55 (50.22%), 109 were female (48.44%), and 3 were non-binary individuals (1.33%), with an
56 average age of 36.24. We evaluated non-response bias by examining differences between early
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and late respondents across all variables. Our findings indicate that there was no indication of response bias in our analysis.

Measures

For all measurements, we utilised a 7-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (7). Table I outlines the scale items corresponding to each key construct.

Insert Table I about here

Purchase intention. Previous research suggests that purchase intention reflects consumers' inclination and willingness to acquire a product or service. Consistent with validated scale propositions (Zhao et al., 2020), we assessed purchase intention using four subjective measures related to consumers' behaviour, perceptions, and attitudes toward a product ($\alpha = 0.888$).

Perceived price fairness. In assessing perceived price fairness as a mediating variable, we utilised three items derived from prior research (Zhang et al., 2024, Büyükdağ et al., 2020). Price invariably stands as a pivotal concern for consumers prior to making purchasing decisions, as it serves as a crucial determinant in the marketplace. This stems from the economic principle wherein price represents the constraint within which consumers trade-off products to maximise utility, operating within an information-transparent marketplace ($\alpha = 0.798$).

Perceived product quality. Building upon prior research (Konuk, 2019), we operationalised perceived product quality to encompass the product's capacity to fulfil its functions, including durability, reliability, performance, strength, ease of packaging, and repairability. We gauged product quality through four items assessing perceptions of quality ($\alpha = 0.886$).

Perceived product features. Perceived product features involve the consumer's cognitive evaluation and understanding of the product's attributes. Perceived product features

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3 are influenced by individual preferences, expectations, prior experiences, and the context in
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5 which the product is evaluated. We assessed perceived product features through three items,
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8 considering them as attributes of a product designed to fulfil consumers' needs and desires (α
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10 = 0.877) (Zhang et al., 2019). These features encompass the satisfaction derived from owning,
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12 using, and leveraging the product. In the context of smartphones, features encompass both
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14 hardware and software components.
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17 *Sustainable community influence.* Sustainable community influence was assessed based
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19 on individual shifts in actions, feelings, thoughts, attitudes, or behaviors influenced by
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21 interactions with others or groups, aligning with previous studies (Varshneya et al., 2017). We
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23 used four specific items to measure this influence, focusing on socialization, shared social
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25 values, peer influence, and family guidance in relation to the purchase of second-hand
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27 smartphones ($\alpha = 0.875$).
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30
31 *Control variables.* We controlled for respondents' gender, income, and age in our study to
32
33 account for key demographic influences on consumer behaviour in the reuse market (Islam et
34
35 al., 2021). Gender variations in technology adoption have been documented, with studies
36
37 highlighting differences in usage patterns between males and females (Sobieraj and Krämer,
38
39 2020). Income is also critical, impacting purchasing power and preferences, with higher-
40
41 income individuals often opting for premium tech models (Bai et al., 2020). Additionally, age
42
43 plays a key role, with generational disparities influencing technology adoption and usage
44
45 behaviours (Blut and Wang, 2020). **While not central to our hypothesised model, controlling**
46
47 **for these variables ensures a more robust estimation of the core relationships.**
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54 **Analysis and Results**

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56 We employed partial least squares structural equation modelling (PLS-SEM) to
57
58 evaluate our measurement model and test hypotheses. PLS-SEM was chosen for our study
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3 because it effectively models complex relationships by focusing on variance, helping to avoid
4
5 problems like inadmissible solutions and factor indeterminacy (Hair Jr. et al., 2022).
6
7 Furthermore, our conceptual model delves into a mediation framework, exploring the
8
9 intermediary role of perceived price fairness between perceived product quality, perceived
10
11 product features, and sustainable community influence on purchase intention. PLS-SEM offers
12
13 several advantages suited to our study. By optimising local-level constructs, it enables more
14
15 accurate predictions and increases statistical power, thereby enhancing the explanatory power
16
17 of our findings.
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20

21 **Measurement model**

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23
24 Table I demonstrates that all factor loadings exceed 0.702, indicating satisfactory
25
26 indicator reliability. Additionally, the minimum Cronbach's alpha and minimum composite
27
28 reliability (CR) values, as depicted in Table I, stand at 0.798 and 0.806, respectively, meeting
29
30 the criteria for acceptable construct reliability (Hair Jr. et al., 2022). Moreover, all constructs
31
32 exhibit average variance extracted (AVE) values above 0.5, with a minimum AVE of 0.712,
33
34 signifying a convergent validity (Hair Jr. et al., 2014).
35
36
37

38 To ascertain discriminant validity, we employed both the Fornell-Larcker criterion and
39
40 the heterotrait-monotrait (HTMT) test. According to the Fornell-Larcker criterion (refer to
41
42 Table II), the square root of the AVE for each construct surpasses its highest correlation with
43
44 any other construct. Additionally, as shown in Table III, the maximum HTMT value stands at
45
46 0.852, which falls below the 0.90 threshold (Hair Jr. et al., 2014). These results collectively
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48 support the discriminant validity of the measures utilised in our study.
49
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51 We assessed model fit using the Standardized Root Mean Square Residual (SRMR) and the
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53 Normed Fit Index (NFI) (Hair Jr. et al., 2022). The SRMR measures the average discrepancy
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55 between observed and expected correlations, serving as an absolute indicator of fit to avoid
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57 model misspecification. A value below 0.10 or 0.08 (in a more conservative approach) is
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3 considered favourable. Our SRMR value is 0.061. The NFI evaluates the overall fit of the
4
5 model to the data. It evaluates the proportion of improvement in model fit compared to a null
6
7 model, with values ranging from 0 to 1. Higher NFI values indicate better fit. Our model's NFI
8
9 value is 0.904.
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11
12 *Insert Table II about here*

13
14 *Insert Table III about here*

15 16 17 **Controlling for common method bias**

18
19 To evaluate common method bias (CMB), we employed two distinct methods. Initially,
20
21 we conducted a comprehensive collinearity test (Kock, 2017). As illustrated in Table IV, all
22
23 inner variance inflation factors (VIFs) remained below the 3.3 threshold. The highest inner VIF
24
25 value recorded was 3.295. Subsequently, we evaluated the conceptualised constructs for CMB
26
27 through Harman's single-factor test (Fuller et al., 2016). This involved loading all the items of
28
29 the study constructs into an exploratory factor analysis. The outcome revealed that no single
30
31 factor accounted for more than 44% of the covariance among the variables.
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36 *Insert Table IV about here*

37 38 **Analytical model**

39
40 The path coefficients in the inner model of the PLS-SEM were assessed using the 5000
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42 sub-sample bootstrapping method, following the recommendation of Hair Jr. et al. (2014). As
43
44 depicted in Table V, the coefficients of determination (R^2) for purchase intention (0.529, $p <$
45
46 0.001) and perceived price fairness (0.605, $p <$ 0.001) both surpass the recommended threshold
47
48 of 0.10 (Hair Jr. et al., 2022), indicating a significant relationship between the constructs under
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50 investigation.
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54 *Insert Table V about here*

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56 We employed the cross-validated predictive ability test (CVPAT) to assess the model's
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58 out-of-sample prediction errors, ensuring robust generalisation performance and guarding
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3 against issues of overfitting or underfitting in partial least squares (PLS) modelling (Lienggaard
4 et al., 2021). This method was favoured over the PLSpredict approach due to its lack of an
5
6 overarching inferential test to ascertain the significant superiority of predictive capabilities in
7
8 alternative models relative to established ones (Hair Jr. et al., 2022). Table VI presents a
9
10 comparison of the average loss values of PLS-SEM predictions with those of naive indicator
11
12 averages (IA) and a linear model (LM) forecast. To demonstrate superior predictive
13
14 capabilities, the difference in average loss values should be significantly less than zero. Our
15
16 analysis indicates that while PLS-SEM predictions outperform the naive IA prediction
17
18 benchmark and conservative LM for perceived price fairness. The PLS-SEM predictions
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20 outperform the naive IA prediction benchmark for purchase intention, but they fall short of the
21
22 conservative LM prediction benchmark.
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29 *Insert Table VI about here*

30
31 Hypothesis 1 posits that the perceived price fairness mediates the relationship between
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33 perceived product quality and purchase intentions. The results in Table V demonstrate a
34
35 significant positive relationship between perceived product quality and perceived price fairness
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37 ($\beta = 0.257, p < 0.001, f^2 = 0.066$), perceived price fairness and purchase intention ($\beta = 0.722,$
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39 $p < 0.001, f^2 = 1.081$), and an indirect effect of perceived product quality on purchase intentions
40
41 through perceived price fairness ($\beta = 0.186, p < 0.001$) with a 95% confidence interval: 0.084
42
43 - 0.291. Controlling for perceived price fairness, the direct relationship between perceived
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45 product quality and purchase intentions is significant ($\beta = 0.186, p < 0.001$).
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50 Hypothesis 2 predicts that perceived price fairness mediates the relationship between
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52 perceived product features and purchase intentions of second-hand smartphones. The results in
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54 Table V demonstrate a significant positive relationship between perceived product features and
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56 perceived price fairness ($\beta = 0.232, p < 0.01, f^2 = 0.051$), perceived price fairness and purchase
57
58 intention ($\beta = 0.722, p < 0.001, f^2 = 1.081$), and an indirect effect of perceived product features
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3 on purchase intentions through price ($\beta = 0.168, p < 0.01$) with a 95% confidence interval:
4
5 0.048 - 0.280. Controlling for perceived price fairness, the direct relationship between
6
7 perceived product features and purchase intentions is significant ($\beta = 0.168, p < 0.01$).
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10 Hypothesis 3 predicts that perceived price fairness mediates the relationship between
11
12 sustainable community influence and purchase intentions of second-hand smartphones. The
13
14 results in Table V demonstrate a significant positive relationship between sustainable
15
16 community influence and perceived price fairness ($\beta = 0.123, p < 0.05, f^2 = 0.029$), perceived
17
18 price fairness and purchase intention ($\beta = 0.722, p < 0.001, f^2 = 1.081$), and an indirect effect
19
20 of sustainable community influence on purchase intentions through perceived price fairness (β
21
22 = 0.089, $p < 0.05$) with a 95% confidence interval: 0.023 - 0.165. Controlling for perceived
23
24 price fairness, the direct relationship between sustainable community influence and purchase
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26 intentions is significant ($\beta = 0.089, p < 0.05$).
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30 **Discussion**

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33 Our results indicate that perceived price fairness strengthens the relationship between
34
35 perceived product quality and purchase intentions, highlighting its pivotal role in influencing
36
37 purchase decisions for second-hand smartphones in rural markets. While perceived product
38
39 quality shapes initial interest, it alone may not suffice if prices are deemed unfair (Alkaabi,
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41 2022). Fair pricing not only enhances perceived value by aligning with consumer expectations
42
43 but also promotes trust (Mukherjee and Pandelaere, 2023). This transparency in pricing signals
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45 integrity and fairness from sellers, crucial for converting positive quality perceptions into actual
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47 purchases (Alnes and Haugom, 2024). Therefore, emphasizing perceived price fairness not
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49 only reinforces consumer confidence but also promotes cognitive consistency, leading to
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51 higher satisfaction and intent to purchase.
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56 Our findings also suggest that perceived price fairness plays a crucial role as a mediator
57
58 between perceived product features and the purchase intentions of second-hand smartphones,
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2
3 echoing similar patterns observed in studies on second-hand goods (Zhang et al., 2024).
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5 Consumers assess the value of these devices based on their perceived features in relation to
6
7 their price. The perceived features of second-hand smartphones significantly influence
8
9 consumer decisions by blending practical utility with emotional appeal (Gilal et al., 2024).
10
11 Attributes such as camera quality, processing speed, and durability not only shape perceptions
12
13 of functionality and reliability but also evoke feelings of satisfaction and status (Chen et al.,
14
15 2023). We show that, this influence is pronounced in rural areas, where limited access to
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17 diverse products enhances the importance of features like battery life and durability, which
18
19 play pivotal roles in consumer choice and pricing dynamics.
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24 Our findings on the influence of sustainable communities in rural settings offer new
25
26 insights into consumer purchase intentions. These communities embed environmental
27
28 awareness, foster social norms, and build trust in sustainable practices (Varshneya et al., 2017).
29
30 Advocacy for second-hand smartphones, coupled with community endorsements, not only
31
32 educates consumers about environmental benefits but also enhances confidence in product
33
34 quality and reliability (Ek Styvén and Mariani, 2020). This trust, crucial in areas with limited
35
36 market access, bolsters purchase decisions. However, perceived price fairness is essential; even
37
38 with strong community support, unfair pricing can undermine the impact of social
39
40 recommendations (Alnes and Haugom, 2024, Büyükdag et al., 2020). Aligning perceived price
41
42 fairness with the community's advocacy for sustainability enhances the value proposition,
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44 encouraging consumers to make eco-friendly choices that support broader environmental goals
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46 (Liang and Xu, 2018, Armutcu et al., 2024).
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50
51 While the cognitive mechanisms identified in this study, such as schema-based reasoning,
52
53 social proof, and perceived fairness are likely relevant across rural markets, their relative
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55 influence may be shaped by contextual factors. In New Zealand, cohesive rural communities,
56
57 a strong sustainability culture, and expanding digital infrastructure likely amplify these effects.
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Theoretical implications

Our research contributes to the growing literature on cognitive schemas in rural consumer decision-making (Liang and Xu, 2018, Arunachalam et al., 2020), challenging the assumption that rural consumers rely primarily on objective product attributes when evaluating second-hand goods. We demonstrate that subjective perceptions, rooted in prior experiences, social proof, and community influence, play a pivotal role in shaping consumer decision-making, particularly in contexts where access to technical information is limited (Liao et al. 2022). While existing models of consumer choice often prioritise rational assessments of price and product quality, our findings underscore how cognitive shortcuts derived from past interactions with similar products enable rural consumers to mitigate uncertainty and make informed yet heuristic-driven purchase decisions (Gilal et al., 2024, Lee and Kim, 2024, Alnes and Haugom, 2024). This suggests that trust in second-hand markets is not solely built on verifiable quality indicators but on the coherence of past experiences and social validation mechanisms.

A key theoretical advancement lies in our examination of perceived price fairness as a central cognitive anchor in second-hand consumption. Rather than viewing price as a purely transactional element, we argue that consumers assess fairness through a broader interpretive framework, integrating perceived product features and quality with emotional and cognitive consistency (Alkaabi, 2022). This extends existing discussions in consumer psychology by highlighting that price fairness is not just an economic evaluation but a cognitive process that reinforces or challenges schema coherence (Emami et al., 2024). This insight raises important questions about how pricing strategies in second-hand markets influence not only affordability perceptions but also consumer trust and long-term market viability.

Furthermore, our findings challenge the notion that schema adaptation is a purely individual cognitive process by demonstrating the profound role of social mediation in shaping second-hand purchase decisions (Lee and Kim, 2024). Rural consumers exhibit high

1
2
3 responsiveness to contextual cues, particularly the social acceptance of second-hand goods and
4 sustainability messaging (White et al., 2019, Ek Styvén and Mariani, 2020). This has
5
6 significant implications for interventions aimed at shifting consumer behavior, suggesting that
7
8 top-down educational efforts may be less effective than leveraging existing community
9
10 networks and social proof to reshape schemas toward more sustainable and economically
11
12 viable choices (Armutcu et al., 2024).
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17 Our findings further highlight a critical gap in traditional cognitive frameworks, which
18
19 often neglect the evolutionary nature of schemas in response to collective experiences (Marzi
20
21 et al. 2023). While much of the literature assumes stability in consumer decision-making
22
23 processes (Pidduck et al., 2020), we demonstrate that schemas in rural second-hand markets
24
25 are continuously reconfigured through both economic necessity and social influence (Gilal et
26
27 al., 2024). Notably, the integration of environmental consciousness into consumer cognition
28
29 suggests that sustainability messaging can become a culturally embedded heuristic, rather than
30
31 merely a secondary consideration (Mukherjee et al., 2020, Gilal et al., 2024, Emami et al.,
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33 2024).
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40 **Practical implications**

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42 Our findings provide second-hand product sellers, both independent and commercial, with
43
44 valuable insights into the factors influencing consumer purchase intentions in rural areas. Price
45
46 plays a critical role in customers' buying decisions from either type of seller (Makov et al.,
47
48 2019). For independent sellers, customers consider the perceived risk of buying second-hand
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50 products, such as the lack of warranties (e.g., Meta Marketplace) or limited warranties (e.g.,
51
52 TradeMe – New Zealand). Thus, sellers must price their products in relation to the perceived
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54 value to buyers, often using the price of brand-new products as a benchmark for fairness
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56 (Mukherjee and Pandelaere, 2023). For commercial sellers, consumers expect more in terms
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3 of warranties and return policies, such as the one-year warranty offered on Apple refurbished
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5 products.
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8 Businesses can also leverage consumer awareness of environmental issues by emphasizing
9
10 the eco-friendliness of their products, such as promoting the reuse of second-hand smartphones
11
12 (Ek Styvén and Mariani, 2020). Brands can differentiate themselves by aligning their product
13
14 offerings and marketing strategies with sustainable community values and preferences
15
16 (Williams et al. 2024). By highlighting the environmental benefits and cost-effectiveness of
17
18 second-hand products, businesses can tap into the growing demand for sustainable solutions in
19
20 rural communities, where resources and options may be more limited (Gilal et al., 2024).
21
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23
24 Policymakers can promote initiatives that support the second-hand market and reduce
25
26 electronic waste generation (Singh et al., 2022). This includes incentives for recycling and
27
28 refurbishing electronics, such as tax breaks for companies that implement sustainable practices
29
30 or subsidies for consumers who purchase refurbished devices (Islam et al., 2021). Policies
31
32 could also mandate clearer labeling of the environmental impact of electronics, helping
33
34 consumers in rural areas make informed choices. Collaborating with educational institutions
35
36 and local community organizations to raise awareness about the benefits of the circular
37
38 economy and sustainable consumption can further reinforce these efforts, leading to more
39
40 environmentally conscious rural communities (Lewis and Rauturier, 2019).
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47 **Limitations and directions for future studies**

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49 Our findings are specific to rural New Zealand and may not be applicable to other rural
50
51 regions globally due to cultural, economic, and technological differences. **In particular, the**
52
53 **effects of schema-based decision-making, trust, and sustainable community influence may be**
54
55 **magnified by New Zealand's cohesive rural networks, relatively advanced rural broadband**
56
57 **access, and strong national orientation toward sustainability. These features may not be present**
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3 in other rural settings, especially in countries with infrastructural deficits, different
4 consumption norms, or more individualistic decision-making cultures. Future research in other
5 settings can test the transferability of these dynamics, particularly in rural contexts with
6 different trust structures, technological access, or environmental priorities to identify universal
7 versus context-specific patterns (Arunachalam et al., 2020).
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15 Furthermore, the rapidly evolving nature of technology and consumer preferences suggests
16 that longitudinal studies could be beneficial in capturing changes over time and identifying
17 trends in second-hand smartphone purchasing behavior (Alkaabi, 2022). Utilizing
18 experimental designs to study the impact of perceived product features and price fairness on
19 actual purchase decisions could also provide more robust causal evidence (Delladio and Caputo
20 2024).
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29 Future research should aim to refine the framework used in this study by incorporating
30 additional constructs, such as trust in online platforms and the impact of marketing
31 communications, to provide a more comprehensive understanding of consumer behavior in the
32 second-hand market (Jashari-Mani and Zeqiri, 2024). Assessing the effectiveness of various
33 policy interventions, such as subsidies, tax breaks, and educational campaigns, in promoting
34 the second-hand market and reducing electronic waste in rural areas could also provide
35 valuable insights (Singh et al., 2022). Finally, future studies may explore the direct and
36 moderating roles of demographic variables such as income, gender, and age, especially given
37 their documented influence on technology adoption and price sensitivity.
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51 **Ethical approval**

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53 Ethical approval for this research was obtained from the Unitec Research Ethics Committee
54 (UREC) at the Unitec Institute of Technology at the first author's university.
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3 **Declaration of competing interest**
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5 The authors declare that they have no conflict of interest.
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8 **Data availability**
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10 Data will be made available on request.
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Paper Number: JEC-03-2025-0069

Title: *Cognitive Influences in Second-Hand Markets: From Perception to Purchase in Rural Smartphone Consumption*

Dear Professor Caputo,

On behalf of my co-authors, I am pleased to resubmit our revised manuscript titled “*Cognitive Influences in Second-Hand Markets: From Perception to Purchase in Rural Smartphone Consumption*” for continued consideration at the *Journal of Enterprising Communities*.

We are sincerely grateful for the opportunity to revise the manuscript and for the thoughtful, constructive feedback provided by you and the reviewers. The comments were insightful and helped us sharpen the contribution and clarity of our work. In this revised version, we have strengthened the introduction for improved coherence and flow, clarified the paper’s aim and practical relevance, and reinforced our theoretical positioning by expanding on schema theory and addressing alternative perspectives. We also incorporated relevant literature on rural technology adoption and cognitive limitations to better ground the framework in the specific context.

Additionally, we clarified the theoretical and practical implications of the findings, especially in relation to the New Zealand setting, and made the methodological and analytical steps more transparent by explicitly addressing issues such as common method bias and sample inclusion criteria. We also ensured the manuscript was proofread for style and consistency.

All changes made to the manuscript are **marked in red**, and we have included a detailed response letter addressing each reviewer comment. We believe the manuscript has been significantly improved and is now better positioned to make a meaningful contribution to the journal’s focus on enterprise in underserved and rural contexts.

Thank you once again for your consideration and continued support. We look forward to your feedback.

With appreciation,
The Authors

Reviewer 1 Comments	Response to Reviewer 1
The introduction is strong but could be more concise and impactful with better flow between sections. By refining the research gap, tightening the argument, and previewing contributions earlier, the section will better engage readers and set up the study’s significance.	Thank you for the helpful suggestion regarding the introduction. We have revised the section to improve clarity, conciseness, and flow. Specifically, we now articulate the research gap earlier, consolidate background material to avoid redundancy, and provide an earlier preview of the study’s theoretical and empirical contributions. These changes aim to engage readers more effectively and establish the study’s significance from the outset (see pages 3–6 of the revised manuscript).
The paper adequately covers relevant literature but could be more exhaustive in rural consumer behavior and trust theories. Schema theory is well-applied	Thank you for highlighting the need to further strengthen the theoretical foundation of our study. In response, we have expanded the theoretical framework to deepen engagement with the rural consumer behaviour literature, especially around digital

<p>1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16</p> <p>but could be better justified against alternatives. With minor expansions (especially on rural digital adoption and cross-cultural trust), the theoretical foundation would be unassailable. Schema theory is well-applied but could be better justified against alternatives. With minor expansions (especially on rural digital adoption and cross-cultural trust), the theoretical foundation would be unassailable.</p>	<p>adoption and resource constraints in rural New Zealand. We have also integrated recent insights into cross-cultural trust formation within Māori and Pasifika communities. Additionally, we have now more explicitly justified our use of schema theory over alternative frameworks such as the Theory of Planned Behaviour and Signalling Theory, demonstrating its strength in explaining socially mediated cognition in information-scarce contexts (see pages 6–9 of the revised manuscript).</p>
<p>17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33</p> <p>Studies like Park & Lee (2021) and others on rural smartphone adoption barriers or Venkatesh et al. (2019) on technology acceptance in low-infrastructure settings could provide additional support for rural-specific tech adoption challenges.</p>	<p>Thank you for this helpful suggestion. We have revised the manuscript to integrate additional literature that addresses rural-specific technology adoption challenges, particularly in low-infrastructure contexts. These additions strengthen the theoretical framing and provide broader support for our arguments on rural consumer behaviour and digital engagement barriers (see revised sections in the Introduction and Theoretical Framework).</p> <p>A list of added reference have been provided below for easy referral and properly referenced where appropriate throughout the main manuscript.</p>
<p>34 35 36 37 38 39 40 41 42 43 44 45</p> <p>In methodology, author must address common method bias (e.g., via Harman’s single-factor test).</p>	<p>We appreciate the reviewer’s attention to methodological rigour. While we addressed common method bias in the original submission, we recognise that the discussion may not have been sufficiently visible. In the revised manuscript, we have now clearly separated and explicitly labelled the section on common method bias, detailing our use of both Harman’s single-factor test and the full collinearity assessment approach to improve clarity for readers (see revised “Controlling for Common Method Bias” section on page 19)</p>
<p>46 47 48 49 50 51 52 53 54 55 56 57 58 59 60</p> <p>Also, justify online panel use for rural populations (potential digital divide?)</p>	<p>Thank you for this important observation. In the revised manuscript, we have clarified our justification for using an online panel to survey rural populations. Specifically, we now reference the New Zealand government’s Rural Broadband Initiative (RBI), which has significantly expanded internet access across rural areas. Moreover, our sample specifically targets second-hand smartphone users, individuals who are, by definition, digitally engaged. We also implemented geographic screening criteria to ensure that respondents resided in rural towns, as defined by population thresholds. These clarifications are now explicitly stated in the “Data Collection” subsection of the Methods section.</p> <p>(see pages 14–15 of the revised manuscript).</p>

Reviewer 2 Comments	Response to Reviewer 2
<p>Overall, it is well written, and just a minor proofreading/editing is required in term of style.</p>	<p>Thank you for the positive feedback. We have carefully proofread the manuscript and made stylistic and editorial adjustments throughout to enhance clarity, consistency, and flow. We appreciate your guidance in helping us improve the overall presentation of the paper.</p>
MAJOR POINTS:	
<p>First of all, it is necessary to improve and extend the aim of the paper, please provide some insights about the relevance of the paper, why it is different from others, and its implication in the real world.</p>	<p>Thank you for this valuable comment. We have revised the introduction to more clearly articulate the aim of the study, its real-world relevance, and how it differs from existing literature. Specifically, we now highlight the unique contribution of applying schema theory to rural second-hand smartphone consumption, distinguishing our focus on socially mediated cognition and perceived price fairness from more traditional economic or intention-based models. Additionally, we have added an early preview of our contributions. These changes are intended to better engage readers and clarify the paper's significance from the outset (see revised Introduction, pp. 3–6).</p>
<p>Second, I deem the selection of schema theory interesting, but I think further explanation about its suitability in respect of other competing theories may matter. In detail, second-hand consumption has been already explored, with similar constructs, and providing information about its appropriateness in respect of other theory may strengthen the theoretical contribution and make the point of the research.</p>	<p>Thank you for this insightful comment. We agree that clarifying the theoretical positioning of schema theory strengthens the paper's contribution. In the revised manuscript, we have added a concise comparison between schema theory and alternative frameworks such as the Theory of Planned Behaviour and Signalling Theory. This new paragraph (see "Theoretical Framework and Hypothesis Development," pp. 6–9) explains why schema theory offers a more context-sensitive and socially grounded lens for understanding rural second-hand consumption, particularly under conditions of information asymmetry, cognitive constraints, and community-mediated trust. We believe this clarification better justifies our theoretical choice and situates the research more clearly within existing literature on second-hand consumption.</p>
<p>The same applies to hypothesis, is it possible to reinforce them? In particular the ones about gender, age and income (i.e., I expect this last relation to extremely well related to purchase decision).</p>	<p>Thank you for raising this point. To clarify, gender, age, and income were not part of our primary hypothesised relationships but were included as control variables to account for demographic influences on purchase intentions, consistent with prior studies in second-hand and technology adoption research. However, we agree that these factors can meaningfully influence decision-making in rural contexts. To strengthen the paper, we have clarified their role in the methodology section and provided a brief justification for their inclusion as controls based on theoretical and empirical precedents. (see page 17 of the revised manuscript).</p> <p>We have also noted the potential for future research to more directly examine these variables as focal predictors of second-hand consumption. (see pages 25–26 of the revised manuscript).</p>

<p>The sample is large enough to support the analysis, but I think that explaining a bit more the inclusion criteria may be fundamental.</p>	<p>Thank you for this helpful observation. In the revised manuscript, we have expanded the description of our inclusion criteria in the Data Collection subsection of the Methods section. Specifically, we now clarify that participants were required to (1) reside in a rural area (defined as a town with fewer than 2,500 people), (2) have purchased or received a second-hand smartphone within the previous 24 months, and (3) be aged 18 or older. These criteria were built into the survey as screening questions to ensure relevance and consistency with the study's focus on rural second-hand smartphone consumption.</p> <p>(see pages 14–15 of the revised manuscript).</p>
<p>Finally, about the findings and conclusions, it is suitable to explain how results are context dependent and the selection of New Zealand may affect the results.</p>	<p>Thank you for this important point. We have revised the Discussion and Conclusion sections to more clearly explain the context dependence of our findings. Specifically, we now highlight how the characteristics of New Zealand, such as strong rural community cohesion, high digital connectivity due to government infrastructure investments, and a national culture that supports sustainability may amplify the effects of social and cognitive influences in second-hand purchasing. These contextual features are discussed in the Discussion (p. 22) and Limitations and Directions for Future Research (pp. 25-26) sections, where we note that these findings may differ in countries with weaker digital infrastructure, lower community trust, or different cultural attitudes toward reuse and sustainability</p>

The following additional references have been provided

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Cognitive Influences in Second-Hand Markets: From Perception to Purchase in Rural Smartphone Consumption

Table I. Measurement of constructs including validity and reliability

Construct and items	Factor loading
Purchase Intention (Cronbach's $\alpha = 0.888$ CR = 0.889, AVE = 0.749)	
I prefer second-hand smartphones if I find what I'm looking for	0.849
I do search for information about second-hand smartphones	0.899
I Intend to buy a second-hand smartphone	0.887
I Recommend second-hand smartphones to others	0.824
Perceived Price Fairness (Cronbach's $\alpha = 0.798$ CR = 0.806, AVE = 0.712)	
Price is key for me when choosing a second-hand smartphone	0.803
I prefer second-hand phones for their lower cost	0.881
Second-hand phones provide me price variation based on condition	0.845
Perceived Product Features (Cronbach's $\alpha = 0.877$ CR = 0.881, AVE = 0.803)	
I prefer second-hand smartphones with advanced features	0.883
I seek second-hand smartphones with advanced operating systems	0.934
I look for second-hand smartphones with faster internet access	0.870
Perceived Product Quality (Cronbach's $\alpha = 0.886$ CR = 0.886, AVE = 0.815)	
Quality matters most in my second-hand smartphone decision	0.905
Product quality strongly impacts my intention to buy	0.919
Quality is a top factor in drawing me to second-hand smartphones	0.884
Sustainable Community Influence (Cronbach's $\alpha = 0.875$ CR = 0.890, AVE = 0.727)	
Environmental movements affect my choice of a second-hand smartphone	0.805
My environmental beliefs shape my decision for a second-hand phone	0.906
Local community leaders and influencers influence my decision to buy second-hand phones	0.869
Family and friends influence my choice for a second-hand phone	0.828

Source: Authors own creation

Table II. Fornell-Larcker criterion for discriminant validity

Variable	1	2	3	4	5	6	7	8
1 Gender	1.000							
2 Income	-0.059	1.000						
3 Perceived Price Fairness	0.032	-0.103	0.844					
4 Perceived Product Features	-0.051	-0.023	0.690	0.896				
5 Perceived Product Quality	-0.011	0.038	0.687	0.734	0.903			
6 Purchase Intention	-0.038	-0.106	0.721	0.681	0.645	0.865		
7 Sustainable Community Influence	0.017	-0.237	0.468	0.460	0.403	0.659	0.853	
8 Age	0.057	0.298	-0.139	-0.019	-0.081	-0.097	-0.192	1.000

Note: Bold diagonal elements are the square root of Average Variance Extracted (AVE)

Source: Authors own creation

Table III. Heterotrait-monotrait (HTMT) values for discriminant validity

Variable	1	2	3	4	5	6	7	8
1 Gender								
2 Income	0.059							
3 Perceived Price Fairness	0.064	0.130						
4 Perceived Product Features	0.054	0.024	0.819					
5 Perceived Product Quality	0.030	0.040	0.807	0.832				
6 Purchase Intention	0.041	0.113	0.852	0.769	0.726			
7 Sustainable Community Influence	0.029	0.252	0.553	0.508	0.441	0.744		
8 Age	0.057	0.298	0.163	0.054	0.086	0.111	0.204	

Source: Authors own creation

Table IV. Inner variance inflation factor (VIF) values for full collinearity test

Variable	1	2	3	4	5	6	7	8
1 Age		1.362	1.389	1.358	1.376	1.385	1.392	1.394
2 Gender	1.026		1.033	1.026	1.040	1.044	1.039	1.038
3 Income	1.326	1.295		1.308	1.334	1.304	1.333	1.316
4 Perceived Price Fairness	2.142	2.008	1.991		2.862	2.847	2.666	2.746
5 Perceived Product Features	1.663	2.450	2.843	2.814		2.529	2.870	2.909
6 Perceived Product Quality	2.461	1.309	2.599	2.678	2.447		2.770	2.729
7 Purchase Intention	2.696	2.417	3.153	3.165	3.295	3.249		2.654
8 Sustainable Community Influence	1.926	1.724	1.956	1.939	1.928	1.917	1.496	

Source: Authors own creation

Table V. Structural equation modelling results

Endogenous construct		R^2			
Purchase Intention		0.529			
Perceived Price Fairness		0.605			
Structural path	Coefficients	SD	CI 95%		f^2
			LCI	UCI	
Gender -> Purchase Intention	-0.067	0.048	-0.159	0.028	0.009
Income -> Purchase Intention	-0.021	0.060	-0.133	0.100	0.002
Perceived Price Fairness -> Purchase Intention	0.722***	0.052	0.599	0.805	1.081
Perceived Product Features -> Perceived Price Fairness	0.232**	0.081	0.067	0.380	0.052
Perceived Product Features -> Purchase Intention	0.168**	0.061	0.048	0.280	0.018
Perceived Product Quality -> Perceived Price Fairness	0.257***	0.068	0.121	0.392	0.067
Perceived Product Quality -> Purchase Intention	0.186***	0.052	0.084	0.291	0.012
Sustainable Community Influence -> Perceived Price Fairness	0.123*	0.049	0.033	0.224	0.028
Sustainable Community Influence -> Purchase Intention	0.089*	0.036	0.023	0.165	0.303
Age -> Purchase Intention	0.049	0.054	-0.060	0.150	0.004
Indirect effects					
Perceived Product Features -> Perceived Price Fairness -> Purchase Intention	0.168**	0.061	0.048	0.280	
Perceived Product Quality -> Perceived Price Fairness -> Purchase Intention	0.186***	0.052	0.084	0.291	
Sustainable Community Influence -> Perceived Price Fairness -> Purchase Intention	0.089*	0.036	0.023	0.165	

Note: $p < .05$, $p < .01$, $p < .001$; two-tailed test. SD: Standard deviation, CI: Confidence interval, LCI: Lower confidence interval, UCI: Upper confidence interval.

Source: Authors own creation

Table VI. Results of out-of-sample predictive relevance (CVPAT)

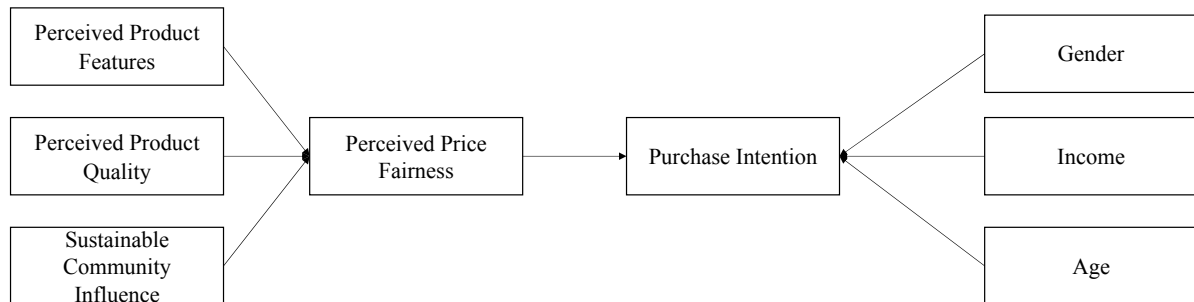
PLS-SEM vs. Indicator average (IA)			
	PLS loss	IA loss	Average loss difference
Perceived Price Fairness	1.178	1.949	-0.770***
Purchase Intention	1.143	1.915	-0.773***
Overall	1.158	1.930	-0.772***
PLS-SEM vs. Linear model (LM)			
	PLS loss	LM loss	Average loss difference
Perceived Price Fairness	1.178	1.276	-0.098*
Purchase Intention	1.143	1.039	0.104†
Overall	1.158	1.141	0.017†

Note: $p \dagger < .10$, $p * < .05$, $p ** < .01$, $p *** < .001$

Source: Authors own creation

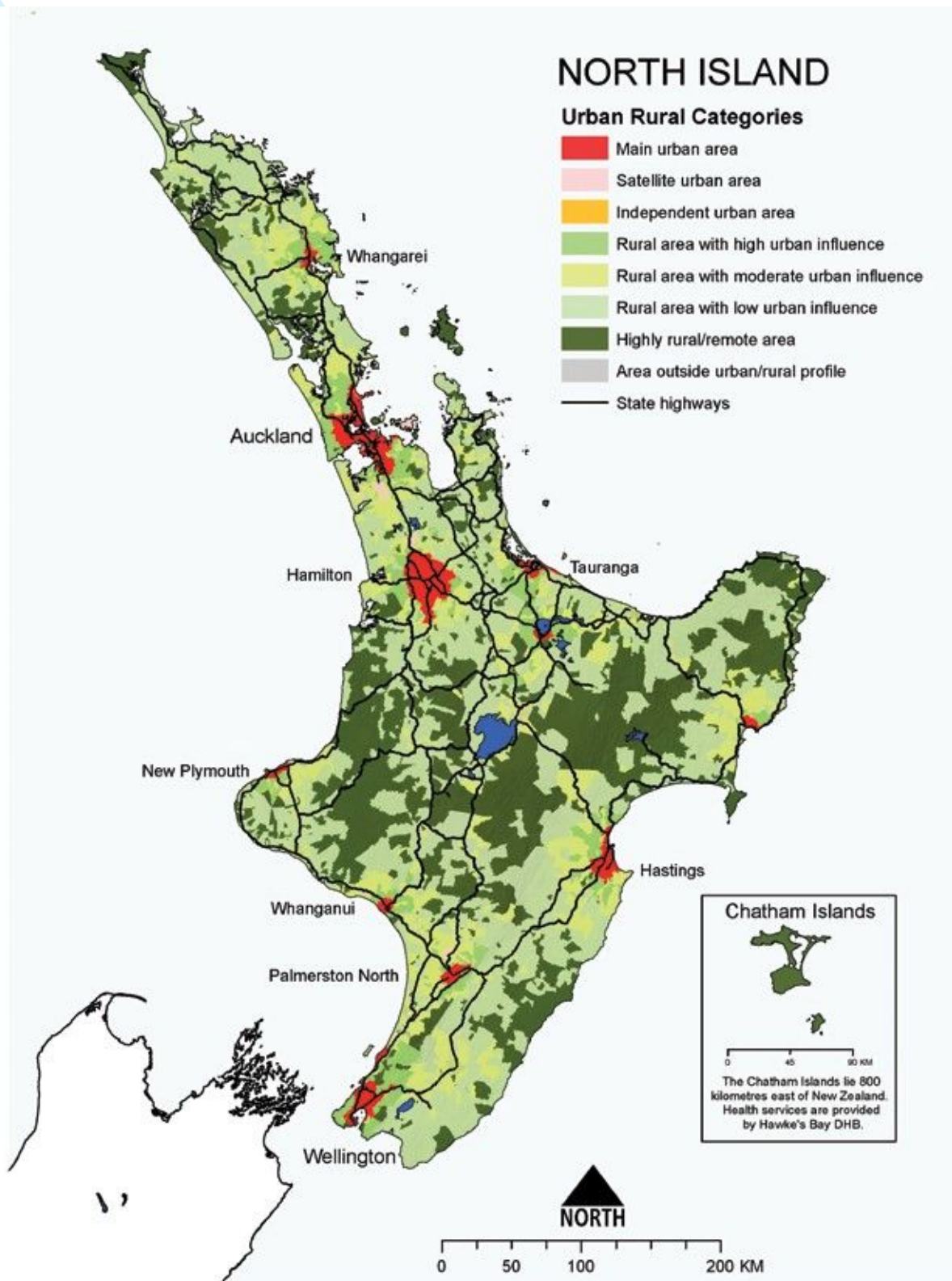
Cognitive Influences in Second-Hand Markets: From Perception to Purchase in Rural
Smartphone Consumption

Figure 1 conceptual framework



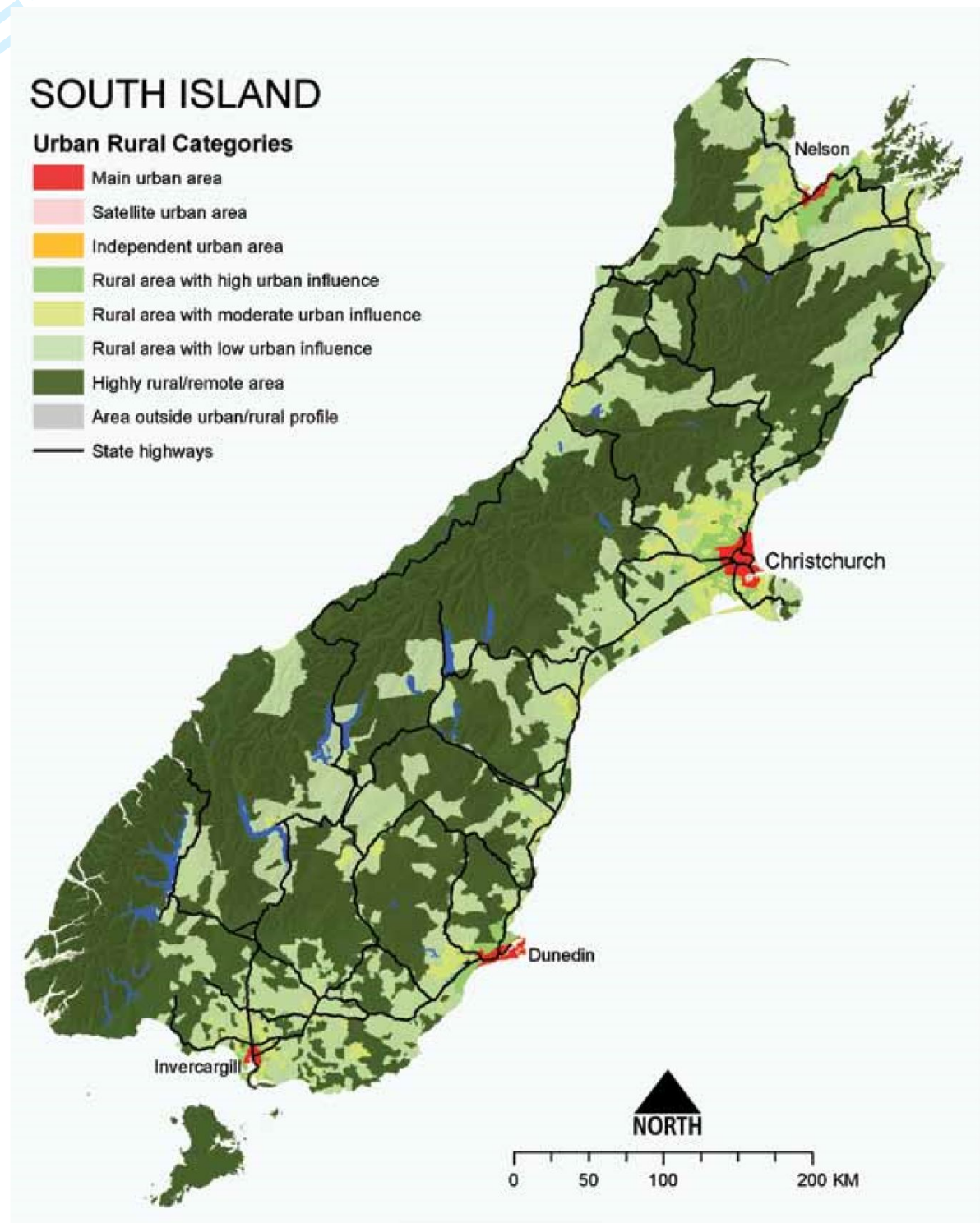
Source: Authors own creation

Figure 2 Rural and urban areas of New Zealand's North Island



Source: Ministry of Health (2024)

Figure 3 Rural and urban areas of New Zealand's South Island



Source: Ministry of Health (2024)