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Fruit Vending Machines as a Means of Contactless Purchase: Exploring Factors Determining US Consumers' Willingness to Try, Buy and Pay a Price Premium for Fruit from a Vending Machine during the Coronavirus Pandemic

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Abstract: During the coronavirus pandemic, buying and consumption patterns of US consumers shifted towards contactless buying. While the topic of online buying is well explored within the existing literature on this topic, purchasing fruit from a vending machine is still yet to be investigated. This exploratory study used quantitative data to examine the factors driving US consumers' willingness to try, buy and pay a premium for fruit from vending machines. An online survey of 391 US consumers was conducted to fill this research gap between 7 July and 10 July 2022. This survey was distributed via Amazon Mechanical Turk, a crowdsourcing platform which is widely used for consumer research. Smart PLS 4 facilitated the Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis, as this method well suited for testing exploratory models with complex relations between the latent variables. Results indicated that COVID-19 pandemic-related benefits, quality benefits, value-related benefits and experiential benefits were the most important predictors that determined willingness to try, buy and pay a price premium when purchasing fruit from a vending machine.

Keywords: COVID-19; fruit; vending machine; preferences; PLS-SEM

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1. Introduction

In December 2019, a new variant of the coronavirus known as SARS-CoV-2 was found in Wuhan, China [1,2]. The highly transmittable virus spread across various countries including the United States of America (US), and the World Health Organization (WHO) declared a global pandemic on 11 March 2020 [3,4]. The US government implemented control measures and health mandates to counteract the spread of the different variants of the virus that occurred during this time [5]. The coronavirus pandemic has led to a recession and impacted lifestyles and consumer behavior [6,7] This can be seen through the changes related to food spending, as well as demand shocks that have occurred. Reportedly, consumers are increasingly shopping for groceries in favor of fast food [6].

Along with the change in demand for groceries, well-being and healthy eating have also been reported as important COVID-19-influenced trends [8,9]. Other studies indicate tendencies towards snacking and the consumption of soul or convenience food [10,11]. Even despite the existing services provided by the food retail industry in the US, food vending machines have provided an important source of convenience foods such as candy, chips, juices, and carbonated beverages with high sugar and fat content [12,13]. Items typically available in vending machines have long shelf lives, are energy dense, and have very limited nutritional value [14]. Over the past decade, vending machines have been subject to scrutiny as the available food items have been found to contribute to the risk of sugar addiction and obesity [13–16]. Since 2010 some schools and worksites in the US have attempted to regulate vending machine offers via policy action [13–16]. However, the widespread availability of healthier food options in vending machines has not yet occurred in the US [16], even though these kinds of vending machines are increasing in popularity in both European and African countries [17–19].

Earlier consumer studies on vending machines were often centered around a dietary context, aiming to mitigate poor food choices amongst consumers and the negative health impacts of these machines [13,16]. However, more recent studies have explored consumer attitudes and perceptions of milk-vending machines [17,18]. Consumer research on stocking vending machines with fresh produce such as fruit and vegetables appears to be largely absent from the extant body of literature. This is despite debate around the increased importance of vending machine use since the occurrence of COVID-19 due to the fact that they can carry everyday necessities such as food items and health kits [20,21]. Additionally, reports focusing on vending machine operators within the US acknowledge the shift in consumer preferences towards more healthy snack options in the last five years [22]. COVID-19 has intensified this shift, forcing vending machine operators to adjust in order to be able to meet this new demand [22]. As a result of these trends, this study aims to fill this research gap and explore key factors that determine US consumer willingness to try, buy, and pay a price premium for fruit from a vending machine.

This introductory section provides the rationale for this paper. The second section features a review of the key factors driving willingness to try, buy or pay a price premium for fruit from a vending machine, and also introduces the hypotheses upon which this research is based. Each hypothesis is underpinned with supporting evidence for the proposed relationships. In the third section details the method used in this study, while the fourth section describes and discusses the Partial Least Square Structural Equation Modeling results. This study then concludes by detailing several best practice recommendations for marketing managers. This final section acknowledges the limitations of this study whilst also providing some directions for future research.

2. Conceptual Review and Hypotheses

2.1. Pandemic Food Shopping and Pandemic-Related Benefits of Fruit Vending Machines (FVM)

COVID-19 has changed the consumption and purchase patterns of US consumers [23,24]. In the US, the significance of online food shopping has increased [25]. In addition to traditional physical purchasing, food retailers now also provide options such as home delivery alongside click-and-collect options [24]. During the worst periods of the pandemic, US consumers reportedly gravitated towards the two latter options. Moreover, physical food shopping has changed to mitigate the risk of infection [26]. Consumers were encouraged to wear masks and keep their physical distance from other buyers [27]. Early in the pandemic US consumers resorted to panic buying which caused stockouts, and this led to purchase restrictions being enforced for specific items such as toilet paper, hand sanitizer, and other essential food items [28,29]. During the coronavirus pandemic, hand sanitizing and contactless payment became more important than ever before for US consumers [27]. Given that FVMs are stocked with fresh fruit and offer consumers a variety of benefits such as ease of use, convince, and an assortment of healthy food options, it is not surprising that these have also been promoted as a purchase option during the COVID-19 pandemic. The ability to see the fruit, the offer of contactless payment, along with the limited risk of exposure to other buyers were very appealing to health-conscious consumers [18,21,30]. Therefore, the following hypotheses are proposed:

Hypothesis 1 (H1): *The impact of COVID-19 is positively associated with US consumer perceptions of the benefits of purchasing from FVMs*.

Hypothesis 2 (H2): *Pandemic-related benefits of FVMs are positively associated with consumers' willingness to (a) try, (b) buy, and (c) pay a price premium for fruit from FVMs.*

2.2. Importance of Intrinsic and Extrinsic Fruit Attributes

Fruit is a highly perishable food product that is comprised of various product attributes which have varying degrees of importance for individual fruit consumers [31–33]. The most important attributes are the color, shape, aroma, variety, texture, and length of the product's shelf life [32–34]. Color and appearance are crucial in purchase situations as they attract the consumer's attention, and also serve as an indicator of both freshness and fruit quality. Similarly, the ability to be able to inspect fruit visually is important for fruit consumers as texture gives an indication of the taste [34–36]. Recent literature in this area makes a distinction between two key attributes; these are the intrinsic fruit attributes and the extrinsic fruit attributes [35,36]. Intrinsic attributes are inherent to the fruit, such as taste, texture, and appearance [31,32]. Extrinsic factors relate to the commercial features of the product such as the method of production, the price point, the packaging, and the country of origin [31,32]. Purchasing fruit requires consumers to make a tradeoff between bundles of fruit attributes in order to maximize their utility [31]. In a vending machine, context utility could be derived from fruit attributes which help to determine the quality and value alongside the safety and freshness [17,18]. Convenience and purchase experience also function as important service attributes [17,18]. Based on these facts, the following hypotheses are proposed:

Hypothesis 3 (H3): *The importance consumers place on intrinsic fruit attributes are positively associated with the perceived safety and freshness benefits that FVMs provide.*

Hypothesis 4 (H4): *The importance consumers place on intrinsic fruit attributes are positively associated with the perceived quality and value benefits that FVMs provide.*

Hypothesis 5 (H5): *The importance consumers place on extrinsic fruit attributes are positively associated with the perceived quality and value benefits that FVMs provide.*

Hypothesis 6 (H6): *The importance consumers place on extrinsic fruit attributes are positively associated with the perceived convenience benefits that FVMs provide.*

Hypothesis 7 (H7): *The importance consumers place on extrinsic fruit attributes are positively associated with the perceived purchase experience benefits that FVMs provide.*

2.3. FVM Benefits

Although he benefits of FVMs are yet to be widely researched, studies on other perishable food products such as milk outline the attitudes of consumers towards buying from vending machines [17,18]. These studies also discuss the benefits associated with the product and the automated service aspects of the machine itself [17–19]. These benefits relate to product, price, and quality attributes. They also relate to the time saved, the economic value, the usefulness of a product, the freshness of the product, and the convenience offered. It has been noted that the emotive and entertainment aspects of vending machines are crucial to the purchase experience [18]. Research in this area has shown that consumers have been found to perceive purchasing from vending machines as an entertaining and fun pursuit [18]. Ultimately, for fresh products, four categories of benefits have emerged; these are safety and freshness, quality and value, convenience, and the experiential benefits which determine consumer intentions to buy the product [18,19]. This has led to the following hypotheses being proposed:

Hypothesis 8 (H8): *Safety and freshness-related benefits of FVMs are positively associated with consumers' willingness to (a) try, (b) buy, and (c) pay a price premium for fruits from a vending machine.*

Hypothesis 9 (H9): *Quality and value-related benefits of FVMs are positively associated with consumer willingness to (a) try, (b) buy, and (c) pay a price premium for fruits from a vending machine.*

Hypothesis 10 (H10): *Convenience-related benefits of FVMs are positively associated with consumers' willingness to (a) try, (b) buy, and (c) pay a price premium for fruits from a vending machine.*

Hypothesis 11 (H11): *Experience-related benefits of FVMs are positively associated with consumers' willingness to (a) try, (b) buy, and (c) pay a price premium for fruits from a vending machine.*

2.4. Conceptual Model

Figure 1 depicts the proposed conceptual model based on the current literature within this topic area. The conceptual model indicates that willingness to try, buy, and pay a price premium for fruit from a vending machine is driven by the consumers' perception of pandemic-related benefits along with safety and freshness-related benefits. This willingness is also related to quality and value-related benefits, convenience, and experience-related benefits. These benefits are influenced by the consumer perceptions of intrinsic and extrinsic fruit attributes, as well as the impact of COVID-19.

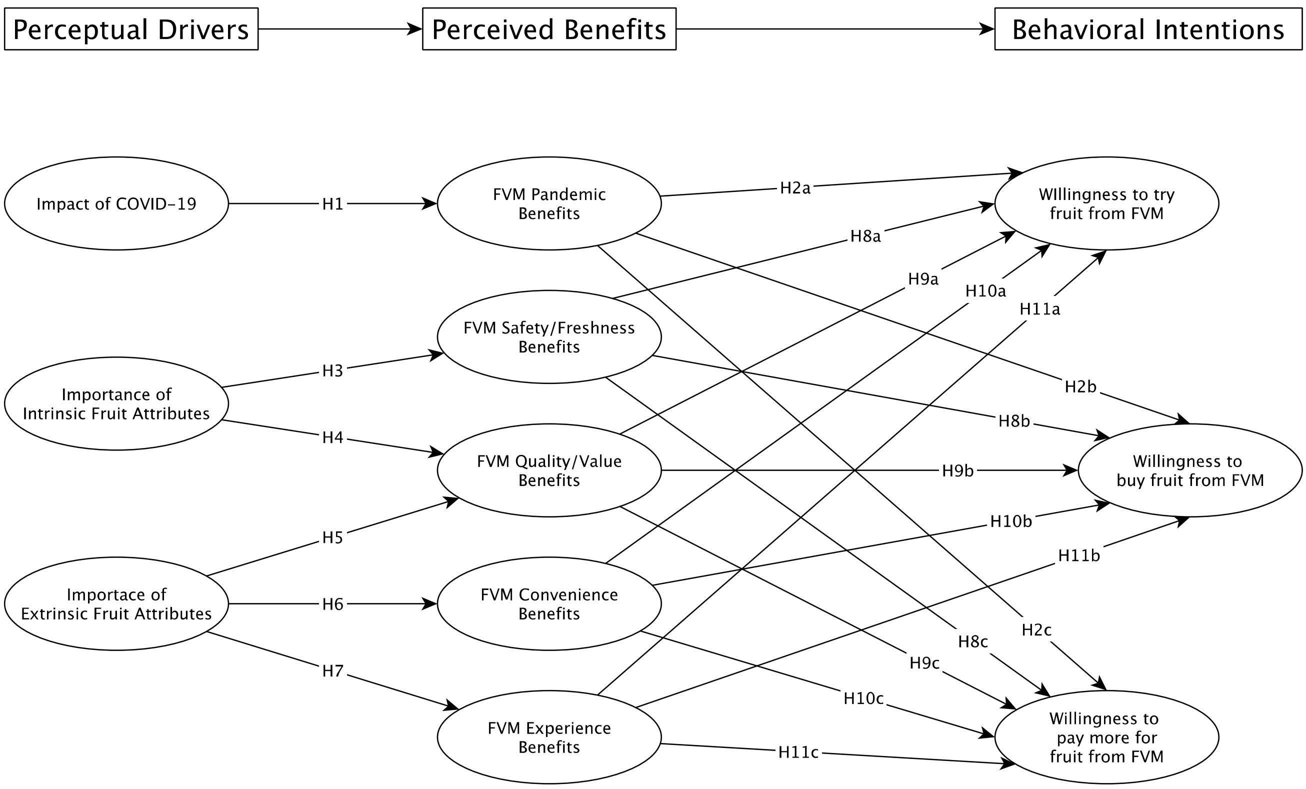

Figure 1. Conceptual Framework. Note: Fruit Vending Machine is abbreviated as FVM.

3. Materials and method

3.1. Study Design

The present study is of explorative quantitative nature and therefore data were obtained from an online survey of U.S. residents. The survey focused on consumer willingness to try, buy, and pay a price premium and was set up in Qualtrics, an online survey tool [37]. US consumers who were at least 18 years of age, resided in the US and purchased healthy food options such as fresh fruit, and had some experience purchasing food from vending machines were targeted as survey participants. Individuals not fulfilling these criteria were excluded from participation. Due to the difficulty in clearly identifying the population of consumers that buy healthy options from vending machines, this study used a purposive sampling approach.

On the crowdsourcing platform Amazon Mechanical Turk (Mturk), a survey link was shared from 6–10 July 2022. Mturk is a marketplace allowing individuals, registered as workers to execute human intelligence tasks (e.g., participating in online surveys) [38,39]. Compared to the general USA—population, these workers are better educated, have often lower household incomes, due to being either unemployed or underemployed [40,41]. Therefore, Goodman and Paolacci (2017), indicate that samples stemming from crowdsourcing platforms such as Mturk are less representative than national probability samples and opt-panels, but superior to college samples, in-person or online convenience samples [38]. Across disciplines, researchers in social science have used Mturk for data collection purposes since its launch in 2005 [41].

The survey respondents were asked about their perception and attitudes towards COVID-19 within the context of food shopping. They were also asked to evaluate the importance of extrinsic and intrinsic fruit attributes, and the perceived benefits obtained from vending machine purchases. Respondents were also asked to indicate their age, gender, income, state of residence, and education in order to facilitate the collection of sociodemographic information.

The survey instrument was pre-tested by five academics at Lincoln University in Christchurch, New Zealand and twenty workers on Mturk. This procedure assured that the correct setup was being used. It also enabled the researchers to check that survey questions and instructions are clearly understood, payment was accurately and fairly provided, and that there are no errors in the survey which could annoy the Mturk workers involved [41,42]. The research context and procedures, including the online survey, were approved by the Human Ethics Committee of Lincoln University (HEC2022-28). Ethics approval and good scientific practices require gaining informed consent from the research participants. An information page, which included a consent form, had to be filled out by each survey participant. Participants werecompletely anonymous, and their information was treated with strict confidentiality. The researchers followed the good practices required for data collection outlined by Litman and Robinson (2021) [41].

Items concerning the convenience, experience, quality, value, freshness and the safety benefits of vending machine were based on questions derived from Kataike et al. (2019) [18] which were then adjusted for the context of fruit. The five-point Likert scale used by Kataike et al. (2019) [18] was further adjusted to a seven-point -Likert scale. The items for the intrinsic and extrinsic attribute questions stem from the authors' research on fruit purchases during the COVID-19 pandemic [32,33]. The COVID-19 impact related items, as well as the items related to the COVID-19 related benefits of vending machines, were created based on the knowledge presented within the existing body of literature. All scale items used a seven-point Likert scale measuring agreement and importance.

400 survey responses were collected. 9 of these responses were completed in much less time than the average of 15 min and were therefore deemed unfit for analysis [43], leaving a total of 391 usable responses for the analysis. A sample size of 391 US residents is suitable to determine the key factors driving their willingness to try, buy and pay a price premium for fruits from a vending machine via Partial Least Squares Structural Equation

Modeling (PLS-SEM) [44,45]. According to Hair et al. (2022), the '10-times rule' stipulates that the sample size should be greater than 10 times the maximum number of inner or outer model links pointing at any latent variable within the conceptual model. This means that for the current research this is 5 links, or a minimum sample size of 50. The ten times rule is a common sample size estimation method, which was why it was used for this study [44].

3.2. Research Approach and Analysis

Standard software packages such as SPSS and SmartPLS were used to conduct the statistical analysis. SPSS served to generate the descriptive statistics used in this study and allowed for characterizing the backgrounds of the survey participants. The evaluation of the research model via PLS-SEM, including hypotheses testing, was facilitated in SmartPLS [44]. PLS-SEM is a suitable approach for exploratory studies building on complex models which aim to identify key constructs driving behaviors or intentions [44,45]. It also allows for robust prediction in the context of asymmetric distributions and interdependent observations. Compared with other regression models, PLS-SEM is advantageous as it does not require data to be normally distributed and can accommodate models with both multi-item and single-item measures [43–45]. PLS-SEM modeling builds on a two-step approach through firstly assessing the measurement model, and then assessing the structural model [44]. The measurement model is dedicated to relationships between the observed data and the latent variables, whereas the structural model focuses on any existing relationships between the latent variables [44].

According to Hair et al. (2022), examining the measurement model entails both reliability and validity checks [44]. These checks include evaluating factor loadings, Cronbach's Alpha, Composite Reliability (CR), and the Average Variance Extracted (AVE) of the multi-item scales. Construct reliability is considered satisfactory when Cronbach's Alpha and the CR scores are greater than 0.6 [44,45]. Convergent validity is reached when items contribute to constructs, and these constructs capture item variation. The contribution of items is then examined via factor loadings on their respective constructs [44]. Hair et al. (2022) outline that loadings must be greater than the threshold value of 0.4 [44]. Likewise, item variation of a construct is deemed sufficient when the AVE exceeds the threshold value of 0.6 [44–46]. The Fornell–Larcker criterion and the Hetero-Trait–Mono-Trait ratio of correlations criterion (HTMT) were used to evaluate discriminant validity [44,47,48]. The fulfillment of the Fornell–Larcker criterion requires each construct's AVE to have a square root that is higher than its correlation with another construct [47,48]. The HTMT check focuses on the correlations of items within a scale and the correlations between items of different scales, which then allows for ratio calculation. If the HTMT ratio is below the threshold value of 0.9, discriminant validity can be confirmed [44]. The Variance Inflation Factor (VIF) allows for identifying multicollinearity in the model. Consequently, when target thresholds are below 5, there is no problem indicated with multicollinearity occurring within the dataset [44,45].

After the successful completion of the measurement model analysis, the structural model was evaluated, and the proposed hypotheses were tested. Based on the work of Hair et al. (2022), the analysis of the structural model required bootstrapping with 5000 iterations. Bootstrapping is a non-parametric procedure allowing for significance testing of the estimated path coefficients and the relationships between variables [44]. The structural model is then evaluated based on the Goodness of Fit (GoF), the explanatory power, and the predictive relevance [44,45]. Further robustness tests were performed once the hypotheses were tested to uncover evidence of endogeneity or unanticipated heterogeneity from sub-samples. For endogeneity, a Gaussian Copula moderator was added to all the proposed relationships in the model (hypotheses), and if significant indicates that some form of endogeneity exists [44]. To test for unanticipated heterogeneity, a multi-group analysis was performed across female and male sub-samples [44].

4. Results

4.1. Sample Description

Table 1 shows the sample demographics. The sample consisted of 49.6% males and 50.4.% females. The overall characterization of the background of the sample can be classified as young, well-educated, and with a low to mid-range income. Most survey participants are under 45 years old, hold a bachelor's or post-graduate degree, and earn an annual pre-tax income in the range of $25,000 to $75,000. The majority of the respondents resided in the South (55.2%), followed by the Northeast (17.9%), Midwest (17.4 %), and Western (9.6%) areas of the United States.

Table 1. Sample demographics and US Census frequencies**.**

	Freq.	%	US Census
Age			
18–24	55	14.1	12
25–34	111	28.4	18
35–44	83	21.2	16
45–54	80	20.5	16
55–64	42	10.7	17
65+	20	5.1	21
Total	391	100	100
Education			
Did not finish high school	8	2.0	11
Finished high school	57	14.6	27
Attended University	37	9.5	20
Bachelor's Degree	222	56.8	29
Postgraduate Degree	67	17.1	13
Total	391	100	100
Household Annual Income			
$0 to $24,999	42	10.7	18
$25,000 to $49,999	133	34.0	20
$50,000 to $74,999	123	31.5	18
$75,000 to $99.999	68	17.4	13
$100,000 or higher	25	6.4	31
Total	391	100	100
Gender			
Male	194	49.6	49
Female	197	50.4	51
Total	391	100	100
Region			
Northeast	69	17.9	17
South	213	55.2	38
Midwest	67	17.4	21
West	37	9.6	24
Total	386	100	100

4.2. Measurement Model

Table 2 shows that all Cronbach's Alpha and composite reliability indicators were well above the required minimum value of 0.6 [44], indicating that construct reliability was achieved. The AVE was higher than 0.5, and factor loadings of all items were higher than 0.6 [44]. Overall, Table 2 confirms that all the composite reliability values indicate good internal consistency reliability and that all latent variables fulfilled the threshold value. This demonstrates that they meet the standard recommended for convergent validity. Furthermore, the means and standard deviations for the single-item measures in the mode.

Table 2. Scale Loadings, Reliabilities, and Convergent Validity for measurement items.

Scales and Items	Mean	Std. Dev.	Factor Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
COVID-19 FVM Benefits	5.18	1.20		0.863	0.901	0.645
A fruit vending machine is beneficial in COVIDian times because there is no human interaction	5.11	1.55	0.793			
A fruit vending machine is beneficial in COVIDian times because the pay is contactless	5.30	1.42	0.789			
A fruit vending machine is beneficial in COVIDian times because I can still visually inspect the product	5.19	1.51	0.837			
A fruit vending machine is beneficial in COVIDian times because I do not have to rely on delivery	5.19	1.50	0.783			
A fruit vending machine is beneficial in COVIDian times because I am not exposed to panic buying	5.07	1.51	0.813			
FVM Convenience Benefits	5.41	1.08		0.767	0.865	0.682
I would save time if I purchased fruit from a vending machine	5.23	1.44	0.796			
I think buying fruit from a vending machine would be convenient	5.47	1.28	0.866			
It would be easy to buy fruit from a vending machine	5.52	1.21	0.814			
FVM Experience Benefits	4.94	1.44		0.864	0.917	0.787
I think buying fruit from a vending machine would be fun	5.17	1.50	0.878			
I think buying fruit from a vending machine would be exciting	4.88	1.66	0.903			
It would be a sensory stimulating experience to buy fruit from a vending machine	4.74	1.73	0.880			
FVM Quality/Value benefits	4.99	1.36		0.869	0.920	0.793
I think fruit sold in a vending machine would be of good quality	5.10	1.49	0.873			
Fruit sold at a vending machine would be affordable	5.00	1.55	0.900			
Fruit sold at a vending machine would be good value for money	4.85	1.55	0.898			
FVM Safe and Fresh Benefits	5.21	1.19		0.827	0.897	0.743
I think buying fruit from a vending machine would be safe	5.20	1.29	0.868			
I think that the fruit offered in a vending machine would be fresh	5.03	1.54	0.861			
It would be useful to have fruit available in vending machines	5.36	1.34	0.858			
Impact of COVID-19	5.10	1.30		0.864	0.902	0.649
Since COVID-19, I actively avoid contact with other people in the supermarket	5.01	1.61	0.862			
Since COVID-19, my preference for online shopping has increased	5.23	1.53	0.766			
Since COVID-19, my preference for contactless payment has increased	5.26	1.58	0.814			
Since COVID-19, I wear a mask and gloves for food shopping	4.98	1.78	0.810			
Since COVID-19, I disinfect more	5.00	1.59	0.772			
Importance of Intrinsic Attributes	5.41	0.97		0.767	0.851	0.588
Importance that the color of the fruit skin is intense	5.12	1.30	0.789			
Importance that fruit smell is appealing	5.51	1.17	0.780			
Importance that fruit texture is attractive	5.53	1.26	0.803			
Importance that fruit skin is free of optical blemishes	5.53	1.32	0.691			
Important of Extrinsic Attributes	5.22	1.18		0.850	0.893	0.626
Importance that fruit labeled as sustainable	5.10	1.51	0.862			
Importance that fruit is labeled as organic	5.01	1.64	0.801			
Importance that fruit is packaged conveniently	5.29	1.43	0.828			
Importance that fruit packaging is minimal	5.20	1.42	0.728			
Importance that fruit has a long shelf life	5.47	1.41	0.728			
Willingness to Consume from a FVM (Individual items)						

I am willing to try fruit from a vending machine	5.37	1.38
I am willing to buy fruit from a vending machine.	5.35	1.40
I am willing to pay a price premium for fruit from a vending machine	4.70	1.84

Note: Fruit Vending Machine is abbreviated as FVM.

Table 3 shows that the discriminant validity requirements were fulfilled for all constructs. All HTMT ratios were below 0.90, and for the Fornell–Larcker criterion the cross-loadings were less than the diagonal values [44,47,48]. The VIF scores ranged from 1.00 to 3.19, with an average VIF score of 2.16, indicating that multicollinearity was not problematic [44].

Table 3. Fornell–Larcker Criterion, and Hetero Trait–Mono Trait Ratio.

Fornell-Larcker Criterion	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**
A COVID-19 FVM Benefits	0.803							
B FVM Convenience Benefits	0.593	0.826						
C FVM Experience Benefits	0.604	0.608	0.887					
D FVM Quality/Value benefits	0.646	0.620	0.746	0.890				
E FVM Safe and Fresh Benefits	0.659	0.631	0.671	0.750	0.862			
F Impact of COVID-19	0.683	0.411	0.442	0.464	0.465	0.805		
G Importance of Intrinsic Attributes	0.494	0.486	0.442	0.425	0.419	0.526	0.767	
H Important of Extrinsic Attributes	0.592	0.404	0.512	0.534	0.458	0.571	0.654	0.791
Heterotrait-Monotrait Ratio	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**
B FVM Convenience Benefits	0.725							
C FVM Experience Benefits	0.695	0.739						
D FVM Quality/Value benefits	0.742	0.753	0.860					
E FVM Safe and Fresh Benefits	0.776	0.786	0.792	0.884				
F Impact of COVID-19	0.792	0.506	0.511	0.534	0.549			
G Importance of Intrinsic Attributes	0.601	0.632	0.537	0.515	0.517	0.639		
H Important of Extrinsic Attributes	0.688	0.494	0.593	0.619	0.548	0.667	0.803	

Note: Fruit Vending Machine is abbreviated as FVM.

4.3. Structural Model

In this study, the proposed structural model was tested, resulting in a Goodness of Fit (GoF) of 0.556, a Normal Fit Index (NFI) of 0.765, and a Standardized Root Mean Square Residual (SRMR) of 0.062 for the overall sample. These fit indices suggest an adequate model fit. According to Hair et al. (2022), a satisfactory SRMR is below the threshold value of 0.08. Values greater than 0.10 are considered unfit [44]. In terms of the explanatory power, the model's constructs contributed to an R^2 of 0.467 for the pandemic-related benefits of FVM, 0.163 for the convenience-related benefits of FVM and 0.262 for experience-related benefits of FVM. The model constructs also contributed to an R^2 of 0.295 for the quality and value related benefits of FVM, and 0.175 for safety and freshness related benefits of FVM. An R^2 of 0.542 was obtained for willingness to buy, 0.591 for willingness to pay a price premium, and 0.475 for willingness to try fruit from a vending machine. These values explained 47.5% of the variance of willingness to try fruit from a vending machine, 54.2% of the variance of willingness to buy fruit from a vending machine, and 59.1% of the variance of the willingness to pay a price premium for fruit from a vending machine. These R^2 values suggest that the model appears to be equally well suited to explaining behavior representing the lower, moderate, and higher commitment levels exhibited by consumers. The latter findings are unsurprising given the relatively high price point of vending machine products, as well as the likely effects of the economic recession and the associated food price inflation which has recently occurred in the US [6].

Even though these R^2 values in the present model would be classified as weak to moderate, given the exploratory nature of the research the results do provide sufficient explanatory power. The Stone-Geisser criterion Q^2 was utilised to test predictive relevance. Hair et al. (2022) suggest that values above zero indicate good predictive validity, values higher than 0.25 indicate medium predictive relevance, and values higher than 0.50 indicate strong predictive relevance [44]. As all of these values were reported as being higher than zero, the model had adequate predictive relevance, and this is proven by the average score of 0.366, which suggests medium predictive relevance.

4.4. Results from the Hypothesis Testing

The results of the hypothesis testing are shown in Table 4 and Figure 2. It was found that the impact of COVID-19 was positively associated with US consumer perceptions of pandemic-related FVM benefits, supporting H1. The pandemic-related benefits of FVMs and consumers' willingness to try and buy fruit from a vending machine were not found to be positively associated. No support was found for hypotheses H2a and H2b either. However, pandemic-related benefits and the willingness to pay a premium for fruit from a vending machine were found to be positively associated, which meant that hypothesis H2c was supported.

Table 4. Coefficients for Hypothesised Paths.

Hypothesized Relationship	Coefficient	T Stat.	*p* Value
H1: Impact of COVID-19 → Pandemic benefits	0.683	15.43	0.000
H2a: Pandemic-related FVM benefits → willingness to try	0.156	1.84	0.066
H2b: Pandemic-related FVM benefits → willingness to buy	0.134	1.57	0.116
H2c: Pandemic-related FVM benefits → willingness to pay more	0.188	2.71	0.007
H3: Intrinsic fruit attributes → FVM safety/freshness benefits	0.419	6.16	0.000
H4: Intrinsic fruit attributes → FVM quality/value benefits	0.133	1.96	0.050
H5: Extrinsic fruit attributes → FVM quality/value benefits	0.447	6.14	0.000
H6: Extrinsic fruit attributes → FVM convenience benefits	0.404	6.24	0.000
H7: Extrinsic fruit attributes → FVM experience benefits	0.512	9.31	0.000
H8a: FVM safety/freshness-related benefits → willingness to try	0.270	2.61	0.009
H8b: FVM safety/freshness-related benefits → willingness to buy	0.431	4.80	0.000
H8c: FVM safety/freshness-related benefits → willingness to pay more	−0.064	0.79	0.429
H9a: FVM quality/value-related benefits → willingness to try	0.075	0.79	0.432
H9b: FVM quality/value-related benefits → willingness to buy	−0.007	0.09	0.929
H9c: FVM quality/value-related benefits → willingness to pay more	0.483	5.35	0.000
H10a: FVM convenience-related benefits → willingness to try	0.251	3.41	0.001
H10b: FVM convenience-related benefits → willingness to buy	0.197	2.85	0.004
H10c: FVM convenience-related benefits → willingness to pay more	−0.184	2.88	0.004
H11a: FVM experience-related benefits → willingness to try	0.050	0.60	0.551
H11b: FVM experience-related benefits → willingness to buy	0.089	1.17	0.241
H11c: FVM experience-related benefits → willingness to pay more	0.365	4.74	0.000

Note: Fruit Vending Machine is abbreviated as FVM.; $p < 0.05$.

Furthermore, it was found that the importance US consumers place on intrinsic fruit attributes is positively associated with the perceived safety and freshness benefits that FVMs provide, supporting hypothesis H3. In addition, the importance these consumers place on intrinsic fruit attributes is positively associated with the perceived quality and value benefits that FVMs provide, supporting hypothesis H4. Similarly, the importance consumers placed on extrinsic fruit attributes are positively associated with the perceived quality and value benefits, convenience benefits, and experience benefits that FVMs provide, supporting hypotheses H5, H6, and H7.

The positive associations between the safety and freshness-related benefits of FVMs and consumers' willingness to try and buy fruit from a vending machine indicate support for hypotheses H8a and H8b. Hypothesis H8c, which tested the association between safety and freshness-related benefits, was not supported. For the quality and value-related benefits of FVMs, a positive association was found only for the willingness to pay a price premium for fruit from a vending machine, supporting hypothesis H9c. Both hypothesis H9a which tested the associations between the value-related benefits of FVMs, and and hypothesis H9b, which tested consumer willingness to try and buy fruit from a vending machine, were not supported in the results.

The convenience-related benefits of FVMs exhibited positive associations in terms of the consumer willingness to try and buy fruit from a vending machine, supporting hypotheses H10a, H10b. A negative association for paying a price premium for fruit from a vending machine was found, which thereby showed that hypotheses H10c was not supported. The experience-related benefits of FVMs revealed only a positive association for the willingness to pay a price premium for fruit from a vending machine, supporting hypothesis H11c. Hypotheses H11a and H11b were not supported.

Gaussian Copula tests revealed that H3, H8b, and H11b were significantly related to a systematic part of the model's error term at the $p < 0.05$ level of significance. This could indicate a common method bias, or another source of endogeneity. While H11b was not supported, H3 and H8b both involved safety and freshness benefits, so some caution should be observed when making interpretations regarding these particular results. Finally, unanticipated heterogeneity was tested with a multi group analysis, revealing significant differences in H3, H4, and H11a between males and females at the $p < 0.05$ level of significance. Unanticipated differences can weaken hypothesised relationships, but since H3 and H4 were supported, and the relationship with H11a was very small, it is unlikely that unanticipated sub-sample differences between genders was a notable influence.

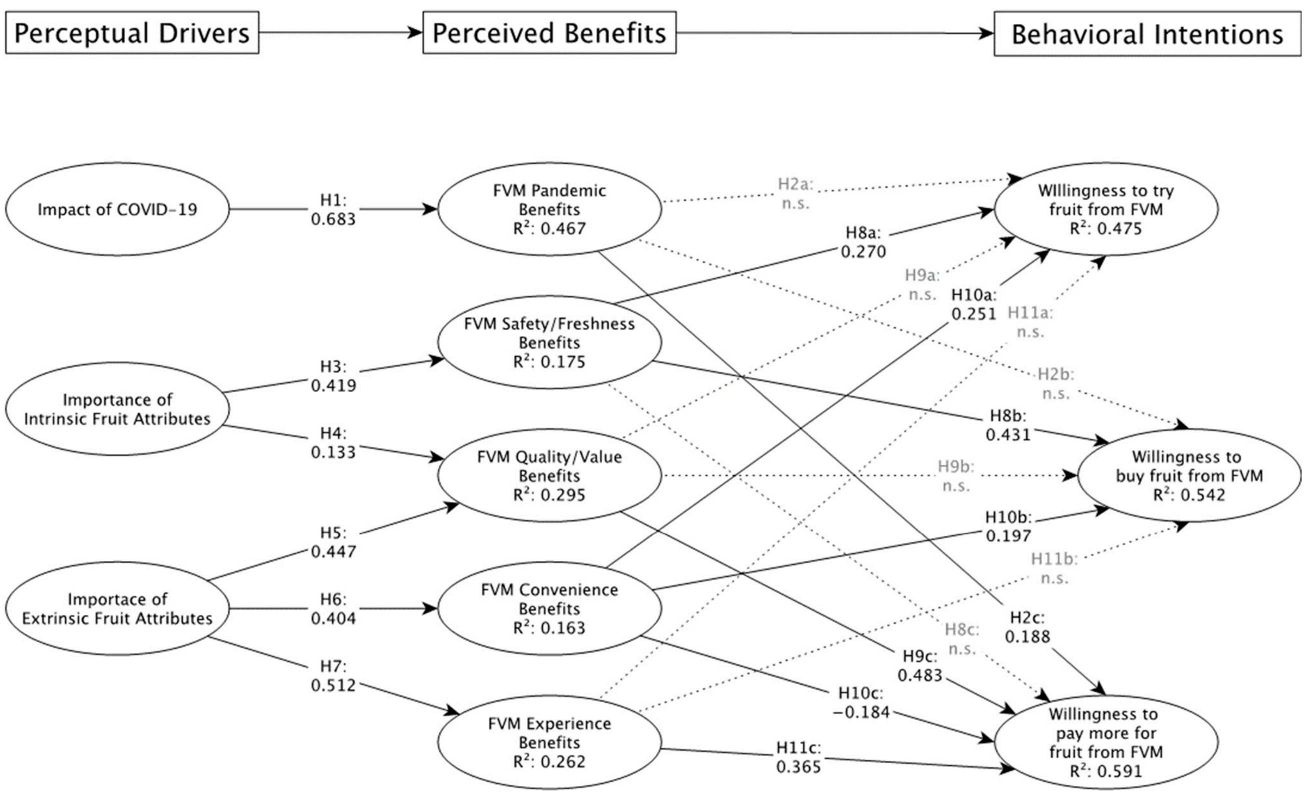

Figure 2. Model with the Results**.** Note: Fruit Vending Machine is abbreviated as FVM.

5. Discussion

These findings related to hypothesis H1 can be explained by the fact that the coronavirus pandemic has likely intensified US consumers' fear of contracting infectious diseases. Vending machines mitigate the risk of infection through limited contact and contactless payment [49]. In addition, consumers are not exposed to stressful retail experiences [26,50]. Previous studies have reported that the payment patterns of consumers have moved toward cashless payment options [51]. Witnessing other consumers panic buying or other inappropriate behavior (such as purposefully coughing and sneezing on fresh produce) is a stressful experience that many consumers would undoubtedly wish to avoid [26].

The pandemic-related benefits of FVMs and consumers' willingness to try and buy fruit from a vending machine were not found to be positively associated, and no support was found for either hypotheses H2a or H2b. However, pandemic-related benefits and the willingness to pay a premium for fruit from a vending machine was found to be positively associated, which meant that hypothesis H2c was supported. This suggests that those who place value on pandemic-related benefits are also willing to pay a premium for fruit from a vending machine.

These results from hypotheses H3 and H4 confirm those of previous studies [17,18,34–36]. The appearance of the fruit is a crucial intrinsic attribute in a purchase situation and is closely associated with quality and value [18,35,36]. The ability to be able to visually inspect fruit is essential for consumers to determine whether the fruit is fresh, safe to eat, and of good quality [52]. For H5, H6, and H7, the positive associations can be explained by the fact that extrinsic fruit attributes are commercial and product-related attributes; these are not inherent to the physical product and can be easily changed to improve the purchase experience [52,53]. Extrinsic fruit attributes such as branding, price, packaging, and labeling serve to provide product information which can influence consumer perceptions of quality [36,53,54] and convenience. This is because these attributes are visual and can be immediately experienced after the purchase has been made from a fruit vending machine.

Food safety and freshness are a requirement for any purchase and consumption situation [55]. Given that US consumers live in a country with comparatively high food safety standards for fresh produce [55,56], they may have a strong preference for safety and freshness. Therefore, they may be willing to try to buy fruit from a vending machine, which explains the results for hypotheses H8a and H8b. The combination of an essential product such as fruit, coupled with the high price point associated with fruit vending machines, may make some consumers reluctant to pay a price premium as shown by the findings from hypothesis H8c.

The results related to hypotheses 9c, H10a, and H10b confirm recent arguments put forward in the current literature in this topic area. There is agreement within the literature that consumers perceive vending machines as being useful in terms of providing quality and convenience options when purchasing perishable food products [18,19]. This is because of the implementation of new technologies [18] such as multi-cart systems to buy multiple items in one transaction, cashless payment, interactive screens, as well as transport belts within the machine which allow for the appropriate handling of fresh produce. These features improve both the efficient delivery and the handling of the product. This in turn adds to the overall quality, convenience, and perceived ease of use experienced by consumers, which directly affects consumer purchase intentions [18]. The negative association related to hypothesis H10c can be explained by the fact that convenience is an essential underlying motive for vending machine purchases. These purchases require consumers to accept paying a price premium already in order to be able to have access to this convenience. The use of technology can also affect the consumer experience by highlighting the fact that buying from a vending machine can be fun, exciting and easy, combining a good purchase experience with immediate product access [18]. These factors have all been shown to influence consumer preferences for buying from a vending machine; they also serve to reinforce the consumer willingness towards paying a price premium for experience-related benefits that was shown in hypothesis 11c.

6. Conclusions

6.1. Theoretical Implications and Suggestions for Future Research

The results of this exploratory study are a valuable addition to the recent body of literature on buying fruit through different distribution channels. Buying from US food retailers at the farm gate and from farmers' markets has been well explored in terms of consumer behavior [57,58], including consumer preferences and their potential drivers or inhibitors. This study examines the recent trend towards buying healthier food options from vending machines. While vending machines are mainly based on convenience, they represent a contactless purchasing option, and interest in them has been boosted by concerns raised by the coronavirus pandemic. Therefore, this research is both timely and relevant for scholars in the disciplines of horticulture, horticultural marketing and economics who might be studying the impacts of COVID-19 on society.

Future research could focus on specific consumer segments, specific fruit offerings, and how willingness to pay varies across segments and offerings. For example, a study comparing rural and urban consumers could be informative as different environments may impact fruit quality, and price expectations could affect consumer purchase decisions. Given the recent literature on vending machine purchases it is inconclusive as to whether rural or urban consumers are more likely to buy healthy snacks from vending machines, so a study which focuses on this would have real merit.

Building on the results of this study it can be anticipated that metropolitan consumers are likely to appreciate the convenience and experiential features of vending machines as life in these cities is busy and technology driven. Other potential directions for future research could investigate portion sizes and the presentation of fruit to maximize the appeal of these products to the point of purchase. This will allow for the enhanced targeting of specific fruit products to consumers, thereby increasing the potential turnover from these vending machines.

6.2. Information for Practitioners

This research provides valuable information for businesses aiming to offer FVMs, such as fruit growers and marketing managers in the US horticultural industry and food retailing. Consumer perceptions of the products and automated services provided by FVMs are important to foster repeat purchase behavior. Fruit growers who wish to operate FVMs as a means of contactless buying need to carefully choose their price point. Food safety and freshness are essential to buying fruit and have been shown in this study to be two of the key underlying reasons why consumers choose to purchase from a vending machine. A price premium appears to be more likely to be achieved through a combination of quality, value, safety and freshness as essential criteria for choosing fruit, and these need to be augmented by experiential elements offered by FVMs. For example, growers could use screens with short video clips showing insights into the fruit production process to educate consumers about fruit varieties, or other more interactive ways to enhance their consumption experience. These could counteract consumer inability to thoroughly investigate the intrinsic and extrinsic attributes of the fruit products concerned, which in turn could help to generate consumer trust [19]. In addition to an improved purchase experience, these videos may also serve to strengthen consumers' perception of fruit quality [19].

6.3. Limitations

Some limitations concerning the data procurement and sampling used in this study need to be acknowledged. The data used in this study originated from a crowdsourcing platform. Samples from platforms such as MTurk are not comparable with representative samples of the US population [40,41], but are superior to convenience samples. This study features a sample that was rather young and well-educated, and the perspectives of elderly consumers are missing from the study. However, younger consumers are the main consumers of vending machine products as these vending machines are largely present in schools and universities. Therefore, recruiting via MTurk was deemed appropriate as the majority of workers on the platform are from this young and well-educated target group [41]. In an effort, to overcome these drawbacks in future studies, quota sampling following the most recent census alongside recruitment and dissemination through the use of opt panel providers may allow for more representative results.

Finally, at a research design level, there are limitations that apply to all cross-sectional data collections. These are namely the inability to make causal attributions, the possibility of common method bias, and the inability to rule out alternative explanations.

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