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A Study of Unmanned Store Adoption among University Students: A Control Variable Perspective

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ABSTRACT

In the past nine years, a significant trend has emerged in the retail sector with the rise of cashier less and unmanned stores. This technological innovation is becoming increasingly widespread across various countries, although its availability remains somewhat limited in Hungary. The current study investigates the extent to which students in Hungarian higher education institutions are willing to adopt this technology. It explores the factors influencing attitudes toward cashierless shopping, using the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) as the theoretical framework. Seven hypotheses were formulated based on a comprehensive review of existing literature and research models. In addition to these core hypotheses, the study also assessed whether three control variables income, gender, and location had an impact on key latent variables within the model. Data collection was conducted via an online questionnaire, which garnered responses from 843 participants. The study employed variance-based structural equation modelling (PLS-SEM) to analyse and test the proposed research model. The results revealed that performance expectancy, effort expectancy, social influence, and hedonic motivation had a strong and positive influence on behavioural intention toward using cashier less stores. Regarding the control variables, significant relationships were identified between income and atmosphere variable, as well as income and price sensitivity. Furthermore, gender was found to have a significant influence on hedonic motivation, suggesting that these demographic factors play a moderating role in shaping attitudes toward unmanned store technology. The findings of this study provide valuable insights for practitioners and policymakers in the retail industry who are considering the implementation of cashier less technology. The diffusion of this technology is expected to grow, making it crucial to investigate factors that influence not only intentions but also the actual use of unmanned stores.

1. Introduction

1.1 Research Background

Over the past two decades, the rapid growth of artificial intelligence (AI) and other immersive technologies has fundamentally reshaped consumer behaviour, transforming technology acceptance

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from a novelty into an everyday necessity [3]. AI has revolutionized the way consumers interact, shop, and engage with services [22; 31], with significant effects on the retail industry, which faces numerous challenges as a result. Since 2015, a new trend has emerged within retail: the development of unmanned, cashierless stores by numerous start-ups [63]. In 2021, the global market size of cashierless convenience stores exceeded $67 million, and it is projected to grow to more than $1.64 billion by 2028 [12]. Although these stores are most prevalent in the United States and Asia, their expansion in Europe is currently underway, with market penetration expected to increase. This technology, driven by AI, has the potential to completely automate traditional retail spaces, minimizing human interaction. The consumer journey in a cashierless store starts with downloading the store's app, registering, and making purchases without the need for traditional checkout processes.

This frictionless experience is powered by AI technologies that monitor consumer behaviour and automate transactions. The rise of cashierless stores has introduced a variety of terms and concepts in both academic and professional discussions. These terms include "cashierless store" Ting [66], "cashierless concept" Ponte and Bonazzi [55], "Amazon Go" Ray et al. [58], and "Just Walk Out technology" Ives et al. [30], the system used by Amazon. Other definitions commonly used in the literature are "unmanned convenience store," "walk-in walk-out store," "frictionless shopping," "smart store," "automated store," "self-service store," "contactless store concept" [26], "no-checkout store" [63], and "staff less store" [62]. The adoption of unmanned, cashierless technologies by retailers is being driven by their ability to provide high-quality service while significantly reducing operational costs. The rise in minimum wages in several countries has further incentivized retailers to adopt this technology [43], as it also eliminates queues, enhancing customer experience [21]. In addition to the operational benefits, cashierless stores have given rise to new business models that challenge traditional retail practices, requiring businesses to adapt.

Despite the progress made in understanding how consumers interact with immersive technologies, there is still a need for further research to fully comprehend consumer behaviour in the context of unmanned technologies [3]. As these technologies disrupt the retail landscape, [10; 58] highlights the importance of continued scientific investigation. This study specifically focuses on Generation Z and aims to explore how unmanned technology impacts consumer behaviour. To conclude, the research model included three control variables income, gender, and location designed to examine their potential influence on latent variables associated with technology adoption. To address key questions, the study asked: (1) How does income influence latent variables? (2) What role does gender play in shaping these variables? (3) To what extent do geographical disparities (location) affect latent variables? To analyse these factors, the study applied Partial Least Squares Structural Equation Modelling (PLS-SEM), revealing the key influences on Generation Z's intention to use cashierless store technology. The findings contribute to the broader understanding of how unmanned technologies are shaping consumer behaviour in a rapidly evolving retail landscape.

2. Literature Review

Retail remains one of the most competitive industries, characterized by the diversity of formats available to meet consumer needs, low barriers to entry, and the ease with which successful business models can be adapted. The current structure of the retail sector is the result of extensive innovation since the mid-20th century, particularly in food retail, where both radical innovation and intensive internationalization have been major trends since the 1980s [61]. The theoretical foundations of retail marketing were laid by Lazer [39], who identified five critical aspects of strategic marketing management for retail organizations: planning, consumer orientation, a systems approach, change management, and innovation. Innovation is emphasized as vital to business success, encouraging research and development in retail practices. Earlier, Alderson [2] argued that differentiation in retail could be achieved through strategies such as price reductions, targeted advertising, product modifications, and the introduction of innovative practices. As markets became more saturated, Kumar et al. [38] later underscored the necessity of incorporating marketing innovation into retail strategies. He suggested that traditional marketing methods alone are insufficient to guarantee success in highly competitive environments. Retailers have responded by adopting innovations across institutional, functional, and technological domains to remain competitive [40; 60].

Digitalization has been a key driver of marketing innovation in the retail sector. The rise of new communication channels, branding strategies, and transaction formats enabled by digital technology has provided retailers with opportunities to enhance customer engagement and redefine their value propositions. For example, multichannel retailing allows businesses to reach consumers across various platforms, removing the constraints of time and location, while location-based services enable real-time, context-specific marketing activities [40]. Competitive strategy formulation in retail hinges on understanding a business's unique competitive advantage, as outlined by [56]. His model suggests that cost leadership, differentiation, focus, and focused differentiation are critical to establishing a competitive edge. These strategies are typically derived from an organization's core competencies, along with resources that are distinctive and not easily replicable by competitors. Kumar et al. [38] found that companies such as Body Shop, IKEA, and Tetra Pak, which pursued radical business innovations, were market drivers. These firms demonstrated that while market-driven processes support incremental innovation, more fundamental, disruptive innovations arise from a market-driving approach. Liu-Thompkins et al. [41] explored the cognitive, affective, and social dimensions of retailer loyalty, concluding that all three factors play crucial roles. They recommended that retailers improve customer loyalty by excelling in merchandising, pricing, and service (cognitive), enhancing the shopping experience to influence emotions (affective), and fostering stronger relationships through social interactions (social).

Among these, emotional influence satisfaction, enjoyment, and brand image had the most significant impact on customer loyalty. In exploring future innovations in retail, Thaichon et al. [65] found that technology-facilitated omnichannel retail, involving consumer interactions across multiple channels, has a prominent role. Technological innovations in retail have also reduced labour costs, with self-checkout systems, service robots, and mobile apps taking over traditional roles previously filled by employees. While these technologies provide cost-saving benefits for retailers, the advantages for consumers remain less certain. Recent advancements in shopping technologies are largely driven by digitalization. Payment methods, online shopping, and smartphone applications are enhancing the shopping experience, with start-ups continually innovating to provide safer, more efficient consumer journeys [63]. Digitalized business models, as highlighted by Mostaghel et al. [49], have also demonstrated that improving customer interaction can lead to higher sales and overall business performance. Additionally, Behl et al. [6] suggest that gamification at store touchpoints can create value for customers. Virtual reality (VR) stores, noted for their interactivity, allow consumers to explore and engage with products in novel ways, which can influence purchasing decisions [48]. On the back-end, innovations like intelligent inventory management systems Miriam et al. [47] help retailers meet increasing consumer demand, optimizing supply chains and operational efficiency. In conclusion, the retail industry has undergone profound changes due to technological advancements, with digitalization driving much of the innovation seen in both customer engagement and business operations. As competition intensifies, retailers will need to continue exploring new strategies to differentiate themselves, leveraging both front-end customer experience enhancements and back-end operational efficiencies to stay ahead in the market.

3. Methodology

3.1 Hypothesis Development

The research model is based on the extended Unified Theory of Acceptance and Use of Technology Model (UTAUT2) [69]. The model estimates whether the included variables influence the intention to use or actual use of the technology under study. In line with the research objectives, the original model was adapted to the specificities of the study. The model included seven latent variables, five based on validated scales by Venkatesh et al. [69]: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and behavioural intention. Five hypotheses were formulated, drawing from articles by [69]; [44; 52]:

H1: Performance expectancy (PE) directly and positively affects behavioural intention (BI) in cashierless smart stores.

H2: Effort expectancy (EE) directly and positively influences behavioural intention (BI) in cashierless smart shops.

H3: Social influence (SI) directly and positively influences behavioural intention (BI) in cashierless smart shops.

H4: Facilitating conditions (FC) directly and positively affect behavioural intention (BI) in cashierless smart shops.

H5: Hedonic motivation (HM) directly and positively influences behavioural intention (BI) in cashierless smart shops.

Unmanned stores mostly have minimalist interior designs and a limited range of products worldwide. A new construct called 'Atmosphere' was created to investigate whether the specific Atmosphere of the stores affects the intention to use them. The sixth hypothesis was formulated as follows:

H6: Atmosphere (AT) directly and positively influences behavioural intention (BI) in cashierless smart stores.

Currently, in Hungary, the penetration of the technology under study does not yet allow respondents to judge the value for money, so the price value latent variable was replaced by the price sensitivity construct [33]. It can be posited that most Hungarian consumers are primarily driven by price considerations [13; 53], and the products sold in the surveyed stores are mostly higher priced. The formulation of the seventh hypothesis was as follows:

H7: Price Sensitivity (PS) directly and negatively affects behavioural intention (BI) in smart shops without cash registers.

Some conceptual corrections were necessary to make the BI construct Venkatesh et al. [69] interpretable in the context of the analysed technology. Our model excluded the actual use variable, as regular use cannot yet be determined in Hungary.

3.2 Primary Data Collection and Data Analysis

An online survey was conducted between February 2023 and January 2024 to assess the adoption of cashierless technology among Generation Z citizens. The target population consisted of individuals born between 1995 and 2010, all of whom were active students in Hungarian higher education institutions and receptive to technological innovations [32]. The survey was distributed across several universities located in the five largest Hungarian cities, yielding a total of 1,030 voluntary responses. A 'snowball method' was employed to reach participants. Initially, the concept of unmanned stores was explained to respondents to prevent confusion during the survey process. Participants were informed that their participation was both voluntary and anonymous, and they were given the option to discontinue their involvement at any time without the need to provide an explanation. The survey featured 29 Likert scale-based statements, ranging from 1 (strongly disagree) to 7 (strongly agree), which were designed to test the research hypotheses. Before data analysis, the dataset was cleaned to remove incomplete or inappropriate responses, such as straight-lining responses where participants selected the same answer for all items. After this process, the final dataset comprised 843 valid responses, which were subsequently analysed using Microsoft Excel and Smart PLS 3.2.9.

The analysis followed the Partial Least Squares Structural Equation Modelling (PLS-SEM) methodology, a common approach in consumer behaviour research. PLS-SEM has been extensively employed in various studies investigating technology adoption and consumer behaviour. For instance, Biswas and Pamucar [7] utilized the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to explore users' perceptions of mobile wallet service providers in India. Similarly, Ghazali et al. [18] applied the UTAUT2 model to examine consumer behaviour in relation to the continued use of AI-based voice assistants (AIVA), particularly in terms of their long-term impact on brand sustainability. Meet et al. [46] investigated the factors influencing the acceptance of massive open online course (MOOC) using an extended UTAUT2 framework. Kim and Kim [35] applied PLS-SEM to examine the effect of implicit theories on consumer perceptions of corporate social responsibility messages, while [19] utilized and expanded the methodology to study the key drivers of purchase intention for luxury goods in the post-COVID period. Furthermore, Khashan et al. [34] employed PLS-SEM to explore the augmented reality (AR) applications adoption in low-income countries.

The data analysis was carried out in three main stages. First, the measurement model was tested to assess reliability and validity. Second, the structural model was estimated, and hypothesis testing was conducted to evaluate the relationships between latent variables. In the final stage, three control variables income, gender, and location were included to determine their potential effects on the latent variables. Income was measured using a five-point scale, with categories ranging from "1-Have difficulty in meeting daily costs" to "5-Live very well and with a high enough income to set money aside." Given the fluctuating consumer price index in Hungary during the data collection period, which ranged from 25.4% to 3.8% Bank [5], the exact income levels of participants were not asked. Instead, the survey focused on respondents' perceptions of their financial situation, capturing how well they managed on their monthly earnings. The location control variable categorized respondents' places of residence into four groups: "1-village; 2-other town; 3-city with county rights; 4-capital city," in line with the classifications used by local governments in Hungary [59]. Through this methodology, the study aimed to provide insights into the factors influencing Generation Z's acceptance of cashierless technology, with a particular focus on the roles of performance expectancy, effort expectancy, social influence, and hedonic motivation. Additionally, the effects of income, gender, and location on these attitudes were explored to offer a more comprehensive understanding of consumer behaviour in this emerging retail context.

4. Results

4.1 Measurement Model

Regarding the measurement model for the reflective constructs, reliability, convergent validity, and discriminant validity were examined (Table 1). Considering the suggested thresholds by Hair et al. [23], all outer loadings exceed 0.7, and all but one Cronbach's alpha (α value) values meet the minimum criteria of 0.6 or a less permissive 0.7. α value of the Atmosphere (AT) construct falls short of the expected value; however, we decided to continue the analysis with this variable due to the proper level of CR and AVE statistics [8; 70]. Furthermore, no better results were achieved excluding

AT from the model. Composite reliability (CR) test (>0.7) and Average variance extracted (AVE) (>0.5) showed proper convergent validity [23; 25; 67]. Facilitating Conditions (FC) construct were excluded due to poor indicator reliability.

Table 1
Construct Reliability, Convergent Validity, and VIF Values

Constructs	Items	Outer Loadings	P Values	α Value	rho_a	CR	AVE	VIF
Performance Expectancy (PE)	PE1	0.834	0.000	0.798	0.800	0.881	0.712	1.614
	PE2	0.837	0.000					1.735
	PE3	0.860	0.000					1.784
Effort Expectancy (EE)	EE1	0.728	0.000	0.800	0.844	0.866	0.619	1.577
	EE2	0.808	0.000					1.644
	EE3	0.849	0.000					1.638
	EE4	0.756	0.000					1.610
Social Influence (SI)	SI1	0.868	0.000	0.862	0.875	0.916	0.784	1.978
	SI2	0.879	0.000					2.363
	SI3	0.908	0.000					2.408
Hedonic Motivation (HM)	HM1	0.910	0.000	0.906	0.911	0.941	0.842	2.968
	HM2	0.928	0.000					3.172
	HM3	0.915	0.000					2.783
Atmosphere (AT)	AT1	0.825	0.000	0.566	0.567	0.822	0.697	1.184
	AT3	0.845	0.000					1.184
Price Sensitivity (PS)	PS2	0.852	0.000	0.799	0.814	0.881	0.712	1.661
	PS3	0.886	0.000					2.075
	PS4	0.791	0.000					1.646
Behavioural Intention (BI)	BI1	0.888	0.000	0.773	0.783	0.898	0.814	1.657
	BI3	0.917	0.000					1.657

Source: Own Calculation

In this paper, the assessment of discriminant validity was conducted using two widely accepted approaches: the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT). These methods ensure that the constructions applied in the model are distinct from one another, confirming the reliability and validity of the model’s latent variables [1; 24; 68]. The Fornell-Larcker criterion, as established by Fornell and Larcker [14], requires that the diagonal values, representing the square root of the average variance extracted (AVE), should be significantly higher than the off-diagonal values in the corresponding rows and columns of the correlation matrix. This condition is necessary to confirm sufficient discriminant validity [23]. The results presented in Table 2 of the study demonstrate that the model meets these conditions, indicating that no issues of discriminant validity are present based on the Fornell-Larcker criterion. However, Henseler et al. [28] emphasized that the HTMT method offers a more robust assessment of discriminant validity than the Fornell-Larcker criterion, as it achieves higher specificity and sensitivity rates. According to Kline (2011), the acceptable threshold for HTMT values is 0.85, while [20; 64] suggests a stricter limit of 0.9. The HTMT values, as shown in Table 3, fall within these threshold limits, confirming that the model has no discriminant validity issues. The use of both the Fornell-Larcker and HTMT methods provides a comprehensive validation of the model's constructions. Before proceeding to estimate the structural model, a multi-collinearity test was performed to ensure that multi-collinearity would not affect the analysis. The variance inflation factor (VIF) values were tested, following the guidelines of Hair et al. [23] which state that VIF values greater than 5.0 indicate potential multi-collinearity issues.

Additionally, Petter et al. [54] proposed a stricter threshold of 3.3, which serves as a more conservative guideline. The VIF values reported in Table 1 of this study are below these thresholds, indicating that multi-collinearity does not pose a problem in the model. Thus, the analysis confirms that the research model is both statistically valid and reliable for further structural evaluation.

Table 2
Discriminant Validity (Fornell-Larcker Criterion)

	AT	BI	EE	HM	PE	PS	SI
AT	0.835						
BI	0.451	0.902					
EE	0.591	0.567	0.787				
HM	0.546	0.639	0.600	0.918			
PE	0.549	0.707	0.657	0.684	0.844		
PS	0.032	0.358	0.140	0.275	0.268	0.844	
SI	0.228	0.519	0.347	0.451	0.496	0.312	0.885

Source: Own Calculation

Table 3
Discriminant Validity (HTMT Criteria)

	AT	BI	EE	HM	PE	PS	SI
AT							
BI	0.675						
EE	0.869	0.679					
HM	0.762	0.756	0.683				
PE	0.817	0.894	0.785	0.804			
PS	0.087	0.453	0.160	0.321	0.335		
SI	0.324	0.629	0.389	0.510	0.595	0.378	

Source: Own Calculation

4.2 Structural Model and Hypothesis Testing

The structural model evaluation was carried out by calculating 5000 resamples, in which the statistical significance of the path coefficient was examined (hypotheses testing). A 95% confidence interval was determined for significant relationships. To assess the model fitness, as Henseler et al. [27] indicated, a standardized root mean square residual (SRMR) should fall below 0.08. The model showed an acceptable level of model fitness, with a SRMR value of 0.065. R^2 was evaluated, and the final model has an adjusted R^2 value of 0.591 ($p=0.000$), suggesting that 59.1% of the variance of Behavioural Intention of cashierless stores can be explained by the six latent variables analyzed. The value of R^2 supports the model's predictive validity. Accordingly, the structural model is moderate (>0.5) [23; 29]; thus, a 0.591 value means moderate explanatory power. Relationships of the research model were analyzed to test six hypotheses. Results show in Table 4 that Performance Expectancy (ß=0.358, p=0.000), Effort Expectancy (ß=0.121, p=0.000), Social Influence (ß=0.161, p=0.000), Hedonic Motivation (ß=0.189, p=0.000) and Price Sensitivity (ß=0.142, p=0.000) significantly influenced Behavioural Intention (BI) while Atmosphere (ß=0.037, p=0.217) have no significant effect on BI variable. Hypothesis four was not tested due to the exclusion of the FC construct. The final proposed model is shown in Figure 1.

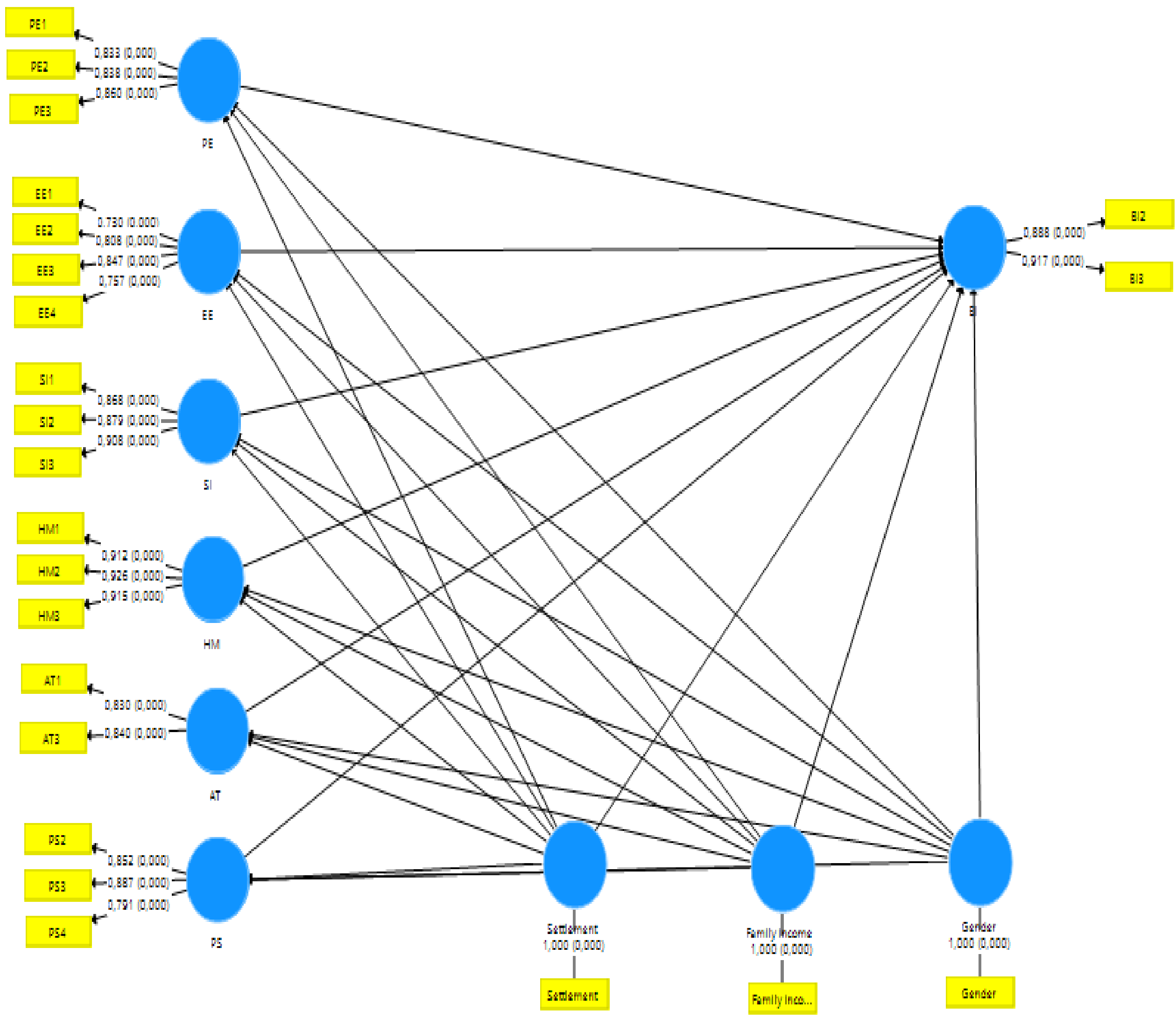

Fig. 1. Conceptual Model of Unmanned Store Technology Acceptance using Control Variables
Source: Own Calculation

Table 4
Bootstrap Results and Hypothesis Results

	Coefficient (ß)	Sample Mean	STDEV	T Statistics	P Values	Hypothesis Validation
PE -> BI (H1)	0.358	0.357	0.038	9.297	0.000*	Supported
EE -> BI (H2)	0.121	0.122	0.029	4.158	0.000*	Supported
SI -> BI (H3)	0.161	0.162	0.028	5.760	0.000*	Supported
HM -> BI (H5)	0.189	0.189	0.037	5.172	0.000*	Supported
AT -> BI (H6)	0.037	0.038	0.030	1.233	0.217	Rejected
PS -> BI (H7)	0.142	0.142	0.027	5.305	0.000*	Rejected because of the Positive Coefficient

Source: Own Calculation

4.3 Effects of Control Variables

In addition to testing the hypotheses, the study included gender control variables, location (respondents' home settlement), and income to examine whether these factors significantly impact the latent variables. Lowry and Gaskin [42] emphasize the importance of analysing control variables that could potentially influence both dependent and independent variables. To account for these effects, the authors suggest drawing a direct path from the control variables to each latent variable in Smart PLS, ensuring a more comprehensive model assessment. The inclusion of these control variables is grounded in prior academic studies, many of which have examined the effects of gender [9; 44; 69; 72; 73] and income [4; 9; 51; 72] on consumer behavior. Location, although less commonly studied, has been explored by Wei et al. [71], who used a rural/urban divide to analyses the impact of location. Most research studies typically focus on how control variables influence the dependent variable alone. However, Lowry and Gaskin [42] recommend also examining their impact on independent variables to ensure a more accurate and nuanced understanding of the control variables' effects. The control variables of age and education were excluded from this study because the sample specifically targeted Generation Z students, making the sample homogeneous in these respects. This exclusion eliminates the potential influence of these factors on the analysis, focusing instead on income, gender, and location. Table 5 presents the results of the control variables' analysis. The results show that income significantly affects both Atmosphere ($p = 0.027$) and Price Sensitivity ($p = 0.029$), while gender significantly influences Hedonic Motivation ($p = 0.000$). These significant relationships suggest that income and gender are important factors to consider when analysing the adoption of cashierless technology, particularly in their effects on key latent variables such as Atmosphere, Price Sensitivity, and Hedonic Motivation. However, no significant relationships were found for the location control variable in this study.

Table 5:
Control Variable Statistics

	Coefficient (ß)	Sample Mean	STDEV	T Statistics	P Values
Income -> PE	-0.031	-0.032	0.033	0.956	0.339
Income -> EE	-0.018	-0.017	0.032	0.544	0.586
Income -> SI	-0.005	-0.005	0.035	0.152	0.879
Income -> HM	-0.055	-0.055	0.032	1.729	0.084
Income -> AT	-0.071	-0.072	0.032	2.205	0.027*
Income -> PS	0.075	0.075	0.035	2.179	0.029*
Income -> BI	-0.008	-0.008	0.023	0.340	0.734
Gender -> PE	-0.003	-0.002	0.034	0.083	0.934
Gender -> EE	-0.012	-0.012	0.034	0.353	0.724
Gender -> SI	0.012	0.013	0.035	0.332	0.740
Gender -> HM	0.159	0.159	0.034	4.689	0.000*
Gender -> AT	0.062	0.063	0.035	1.809	0.070
Gender -> PS	-0.038	-0.037	0.034	1.125	0.261
Gender -> BI	-0.004	-0.004	0.022	0.200	0.841
Location -> PE	-0.060	-0.059	0.035	1.714	0.087
Location -> EE	0.038	0.039	0.035	1.094	0.274
Location -> SI	0.007	0.007	0.035	0.206	0.837
Location -> HM	-0.018	-0.018	0.034	0.539	0.590
Location -> AT	-0.024	-0.024	0.036	0.679	0.497
Location -> PS	0.013	0.014	0.034	0.393	0.694
Location -> BI	-0.026	-0.026	0.023	1.149	0.251

Source: Own Calculation

5. Conclusions

This research aimed to refine the UTAUT2 model in the context of unmanned, cashierless stores, focusing on Hungarian Generation Z students, who, according to Jung et al. [32], represent the primary demographic for this technology. The findings provide valuable insights into the factors that drive the acceptance and adoption of these stores among Generation Z. Additionally, this study investigated the effects of income, gender, and location as control variables to further clarify the relationships between key factors. The results of the study support several hypotheses. Performance Expectancy (PE) had the strongest influence on Behavioural Intention (BI), confirming Hypothesis 1 (H1). This suggests that Generation Z students perceive cashierless technology as beneficial, likely due to its ability to improve flexibility and efficiency in their daily lives. This finding aligns with earlier studies [11; 17; 74], highlighting the importance of performance benefits in technology adoption. Effort Expectancy (EE) also significantly influenced BI, supporting Hypothesis 2 (H2). This implies that Generation Z students find the learning process involved in using cashierless stores manageable, making the technology more appealing. Furthermore, Social Influence (SI) was found to positively impact BI, confirming Hypothesis 3 (H3). The role of social influence, particularly through social media, is especially strong among younger generations, as evidenced by similar findings in studies of autonomous public transport systems [37]. Hedonic Motivation (HM) was also a significant predictor of BI, supporting Hypothesis 5 (H5). The results suggest that Generation Z students enjoy the shopping experience in cashierless stores, which likely motivates them to use such technology. Retailers can capitalize on this by enhancing customer experience through technological innovation, which is critical for Generation Z consumers [45; 57]. However, the study found that Atmosphere (AT) did not significantly affect BI, leading to the rejection of Hypothesis 6 (H6). Generation Z students may prioritize product variety over the store's physical layout, which requires further investigation. Similarly, Price Sensitivity (PS) showed a surprising positive relationship with BI, contradicting Hypothesis 7 (H7). Although Hungarian consumers are generally known to be price-sensitive [15; 36], the added convenience of cashierless stores may justify higher prices for this generation, suggesting a need for further research into this area. Regarding the control variables, three significant relationships were identified. Income influenced both Atmosphere and Price Sensitivity, while Gender significantly affected Hedonic Motivation. On the other hand, Location did not have a verified effect on any of the latent variables. In conclusion, this research provides valuable insights into the factors that influence Generation Z's intention to adopt cashierless stores. The findings can guide retail experts and stakeholders in designing strategies to engage this tech-savvy generation, particularly by emphasizing the convenience and enjoyment that unmanned stores can offer. Further research is needed to explore the nuances of price sensitivity and the role of the store's atmosphere in influencing shopping behaviour in this demographic.

6. Limitations and Future Research

One of the primary limitations of this research is that it only examined intention to use cashierless technology in Hungary, as the actual usage was constrained by the limited number of stores offering this technology. Although Generation Z is familiar with cashierless systems, their availability is currently restricted to Budapest. Given the expected expansion of this market, it is both essential and timely to explore factors that influence not only intentions but also the actual usage of cashierless stores as they become more accessible across the country. Another limitation is the study's focus on Hungarian higher education students, which means the findings may not be representative of the broader Hungarian population. The study's scope was limited to a specific demographic tech-savvy Generation Z students who may exhibit different attitudes compared to other groups, such as Generation X, Generation Y, or those less inclined toward technology. To enhance the robustness and generalizability of future research, it is recommended to expand the sample to include other generations and broader demographics to better capture diverse perspectives on the adoption of cashierless technologies. As technology continues to develop, new latent variables should be introduced into future models to account for emerging factors influencing the adoption of these innovations. Additionally, exploring cross-national differences, especially within the Central-Eastern

European region, would provide valuable comparative insights. The region is poised for growth in cashierless retail technologies, as evidenced by the expansion of the Polish retail chain [50]. Therefore, investigating cultural, economic, and technological differences between nations in this region would enrich the understanding of how cashierless technology adoption varies across contexts. Expanding the scope and considering these limitations will provide a more comprehensive understanding of the factors driving the adoption of cashierless stores and will allow for the development of more targeted strategies for different consumer groups.

Author Contributions

Conceptualization, E.Sz.Sz.; source research, E. Sz. Sz., P. K. K., Sz. R.; methodology, E. Sz. Sz.; formal analysis, E. Sz. Sz.; investigation and data collection, E. Sz. Sz., P. K. K., Sz. R.; data curation, E. Sz. Sz.; writing—original draft preparation, E. Sz. Sz., P. K. K., Sz. R.; writing—review and editing, E. Sz. Sz., P. K. K., Sz. R.; visualization, E. Sz. Sz.; supervision, E. Sz. Sz. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The datasets used and analyzed during the present study are available and adequately anonymized by the corresponding author upon reasonable request.

Conflicts of Interest

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

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