Designing a Dynamic Model for Predicting the Sales of New Electronic Products in the Iranian Market

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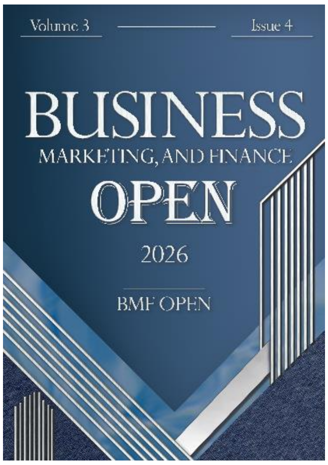

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Abstract: This study aimed to design and validate a system dynamics model for predicting the sales volume of newly introduced electronic products in the Iranian market by integrating consumer perceptions, economic constraints, marketing influences, social feedback, and market-saturation mechanisms. This applied, quantitative study employed a cross-sectional field-survey design and system dynamics modeling. Data were collected from 447 consumers aged 15–29 years in electronic-product stores and shopping centers in Tehran. A researcher-developed questionnaire measured technological innovativeness, product awareness, perceived usefulness, ease of use, product quality, relative advantage, compatibility, brand trust, affordability, price sensitivity, perceived risk, social influence, promotional exposure, electronic word of mouth, purchase intention, and expected early adoption. Construct validity was assessed through exploratory and confirmatory factor analyses, while reliability was evaluated using Cronbach's alpha and composite reliability. Structural equation modeling was used to estimate direct and indirect relationships among the variables. Statistically supported relationships were translated into stocks, flows, delays, and reinforcing and balancing feedback loops. The model was validated through sensitivity analysis, scenario simulation, and comparison of predicted and validation-sample sales outcomes. The structural model demonstrated satisfactory fit and explained 68.4% of the variance in purchase intention and 57.9% of the variance in expected early adoption. Perceived usefulness, electronic word of mouth, affordability, product quality, social influence, and brand trust significantly increased purchase intention, whereas perceived risk and price sensitivity significantly reduced it. Purchase intention was the strongest predictor of early adoption. The dynamic model explained 91.2% of sales-volume variation and produced a mean absolute percentage error of 7.84%. Baseline simulations predicted 28,746 sales in the first year, 61,382 cumulative sales by the second year, and 78,964 sales after 36 months. Combining price reduction with stronger electronic word of mouth generated the greatest sales increase, whereas adverse economic conditions and negative early-user reviews produced the largest declines. The developed system dynamics model provided an accurate and interpretable framework for forecasting new electronic-product sales and demonstrated that affordability, perceived value, consumer trust, online word of mouth, and perceived risk jointly shape the speed and volume of market adoption.

Keywords: Sales forecasting, new electronic products, system dynamics, purchase intention, electronic word of mouth, perceived risk, Iranian market

1. Introduction

The introduction of new electronic products into contemporary markets is accompanied by substantial uncertainty regarding the size, timing, and structure of consumer demand. Unlike established products with stable sales histories, newly launched electronic goods typically have limited or nonexistent historical data, short technological life cycles, rapid rates of obsolescence, strong competitive pressure, and highly heterogeneous consumer responses. These characteristics make conventional extrapolative forecasting methods insufficient, particularly during the early stages of commercialization, when managerial decisions concerning production volume, inventory allocation, pricing, promotion, distribution, and after-sales services must be made before reliable sales records become available. The problem is especially pronounced in markets where economic volatility, import restrictions, exchange-rate fluctuations, uneven purchasing power, and changes in consumer expectations interact with technological change [1, 2]. Consequently, predicting the sales of new electronic products requires a model that can represent not only statistical associations but also the evolving feedback relationships among awareness, perceived value, affordability, adoption, word of mouth, market saturation, and cumulative sales.

Sales forecasting is a central component of marketing planning, supply-chain coordination, inventory management, and financial decision-making. Accurate forecasts allow firms to determine production requirements, reduce excess inventory, prevent stockouts, schedule promotional activities, estimate cash flows, and coordinate relationships with suppliers and retailers. In contrast, inaccurate forecasts may lead to excessive procurement, obsolete inventory, missed market opportunities, inefficient advertising expenditure, and deterioration in customer satisfaction. The importance of sales forecasting has encouraged the development of analytical approaches that combine statistical estimation, machine learning, consumer-behavior analysis, and operational modeling. Recent research has demonstrated that artificial intelligence and hybrid predictive models can improve sales estimation in industries characterized by volatile demand and short product cycles. For example, artificial-intelligence-based forecasting has been applied to pharmaceutical sales in Iran, highlighting the potential of advanced predictive techniques for markets in which traditional forecasting methods may not adequately capture demand complexity [3]. Similarly, smart sales-prediction approaches have been developed for pharmaceutical products by integrating historical and contextual information to support more responsive commercial planning [4]. Hybrid models combining random forests and extreme gradient boosting have also demonstrated strong predictive capability in short-cycle product markets, indicating that nonlinear interactions and temporal dynamics are important for improving forecast accuracy [5].

Despite these developments, the prediction of new-product sales remains fundamentally difficult because historical sales data are either absent or extremely limited at the point of market entry. This problem is particularly important for mobile phones, wearable devices, laptops, wireless accessories, gaming equipment, and other consumer electronics whose commercial success may depend on a brief window of technological relevance. A model developed for newly released and short-term mobile-phone products showed that forecasting performance can be improved when information from comparable products, early sales signals, and product-specific attributes is systematically incorporated into prediction [6]. However, such approaches may still be constrained when the market environment differs substantially from the conditions under which historical analogues were observed. In emerging and unstable markets, demand is shaped not only by product characteristics but also by consumer expectations, perceived economic risk, distribution availability, online reviews, promotional intensity, and rapidly changing prices. Therefore, the forecasting of new electronic-product sales must be embedded in a broader behavioral and market system.

Consumer adoption represents the first behavioral foundation of new-product sales. Sales volume emerges from the aggregation of individual decisions to become aware of, evaluate, purchase, postpone, reject, or recommend a new product. Purchase intention is generally strengthened when consumers perceive the product as innovative, useful, reliable, compatible with their needs, and superior to existing alternatives. Product innovation can directly influence purchasing decisions by offering new functions, better performance, improved convenience, or greater symbolic value. Evidence indicates that product innovation and sales promotion jointly contribute to purchasing decisions, suggesting that a technically attractive product may achieve stronger market performance when its advantages are effectively communicated to potential buyers [7]. In electronic markets, the perceived value of innovation is particularly important because consumers frequently compare recently introduced models with products they already own. The decision to replace or upgrade an electronic device therefore depends on whether the new product provides a sufficiently meaningful relative advantage to justify its cost.

The role of perceived value is also inseparable from the broader marketing mix. Product features, price, place, and after-sales services jointly influence customer evaluations and retention. Research on online retail customers has shown that marketing-mix factors can affect retention through perceived customer value, indicating that the relationship between commercial activities and consumer behavior is mediated by the extent to which customers judge the overall offer to be worthwhile [8]. For new electronic products, after-sales service may be especially consequential because technical complexity increases concerns regarding product failure, warranty coverage, software support, repairs, spare parts, and compatibility. When buyers are uncertain about the durability or serviceability of a product, even strong interest may not be converted into immediate purchasing behavior. Thus, perceived value should be treated as a multidimensional construct incorporating functionality, quality, price, service support, brand assurance, and expected ownership benefits.

Price is among the most influential variables in the diffusion of electronic products. Consumers do not evaluate price only as an absolute monetary amount; they compare it with expected utility, competing alternatives, available income, potential future price reductions, and the risk of rapid obsolescence. In e-commerce environments, presale strategies can influence purchasing decisions by altering perceived opportunity, timing, and loss aversion. Consumers who fear losing a discount or early-access benefit may purchase sooner, whereas those who expect future price reductions may delay adoption [9]. Dynamic pricing research further shows that price and sales effort interact over time and across channels, particularly for products with seasonal or time-sensitive demand [10]. These findings are highly relevant to electronic products, because prices often decline after launch, while promotional incentives, installment plans, and channel-specific discounts may change the timing of demand. A sales-prediction model must therefore represent price as a dynamic constraint rather than as a fixed explanatory variable.

Pricing decisions are also affected by supply-chain arrangements. Wholesale-price contracts, revenue-sharing mechanisms, capacity commitments, and forecast-sharing practices influence how manufacturers and retailers allocate risk and coordinate sales efforts. Under demand uncertainty, the confidentiality of wholesale prices can change competitive behavior and supply-chain performance, demonstrating that sales outcomes are partly determined by information structures and strategic interactions among channel members [11]. Forecast sharing and capacity reservation can likewise affect wholesale contracts and operational decisions, particularly when behavioral responses alter the expected benefits of coordination [12]. Production disruptions further intensify these problems because channel members must balance uncertain demand against uncertain supply, making the design of wholesale-price contracts an important determinant of market responsiveness [13]. In low-carbon supply chains, government subsidies and wholesale-price constraints also influence coordination, pricing, and production decisions, illustrating the broader importance of institutional and contractual conditions in shaping sales performance [14].

Revenue-sharing and quality-related contracts are especially relevant where sales efforts and product attributes must be jointly optimized. A revised revenue-sharing coordination model incorporating sales effort and green quality considerations demonstrates that supply-chain actors may improve performance when incentives are aligned across production, quality, and marketing functions [15]. Similarly, the allocation of responsibility for green-product development between manufacturers and retailers affects product strategy, cost sharing, and market outcomes [16]. Although environmental considerations may not be the primary purchasing criterion for every electronic consumer, green quality, energy efficiency, repairability, and responsible production are increasingly incorporated into product evaluation. Evidence from the literature on green purchasing indicates that consumer attitudes, perceived behavioral control, environmental concern, trust, and product knowledge can shape both purchase intention and actual behavior [17]. A green-marketing model developed to increase pharmaceutical-product sales likewise shows that sustainability-oriented positioning can be integrated into sales strategy and market development [18]. These findings suggest that the prediction of new-product sales may be improved by considering product quality and sustainability as components of perceived attractiveness and legitimacy.

The growth of digital media has transformed how consumers encounter and evaluate new electronic products. Content marketing can move consumers from information exposure to commercial action by increasing engagement, improving brand familiarity, and clarifying product benefits [19]. Inbound marketing similarly emphasizes the creation of relevant and accessible content to attract consumers and support sales, rather than relying exclusively on direct promotional pressure [20]. For electronic goods, product demonstrations, comparison videos, influencer reviews, social-media discussions, and user-generated content can accelerate awareness and reduce information asymmetry. Advertising effectiveness is also influenced by brand credibility and the coherence of sales strategy. The conceptual relationship among advertising, brand credibility, and sales strategy indicates that promotional communication becomes more persuasive when consumers trust the brand and regard the message as credible [21]. Accordingly, advertising does not influence sales in isolation; it operates through awareness, trust, perceived value, and purchase intention.

User reviews represent a particularly important source of dynamic market influence. Consumers differ in their susceptibility to reviews, timing of adoption, product knowledge, and willingness to share experiences. Research on consumer heterogeneity across the product life cycle indicates that the diffusion of user reviews and sales may follow interdependent patterns, with early adopters affecting later consumers and different market segments responding at different stages [22]. This process creates a feedback mechanism: initial adoption produces user experience, user experience generates reviews, reviews alter trust and perceived risk, and these changes influence subsequent adoption. Positive reviews may accelerate sales, whereas negative experiences can produce a self-reinforcing decline in demand. The importance of social-media relationships and loyalty has also been observed in research on sales drivers in emerging markets. Studies of luxury automotive products in Iran have emphasized competitive advantage, customer loyalty, and social-media relationships as central sales drivers [23]. Closely related investigations have similarly identified the interaction of competitive positioning, loyalty determinants, and social-media engagement in shaping sales outcomes [24]. Another formulation of this research has stressed that sales triggers in emerging markets must be understood in relation to customer relationships and competitive-advantage strategies rather than as isolated promotional effects [25].

Consumer trust and perceived risk further determine whether interest is converted into purchase. In technology markets, perceived risk may include financial loss, product malfunction, privacy threats, incompatibility, inadequate service, counterfeit products, and rapid obsolescence. Professional salesperson behavior can reduce uncertainty by providing accurate information, facilitating enjoyable interaction, and strengthening consumer loyalty. Evidence indicates that enjoyable interaction and perceived risk mediate the relationship between salesperson behavior and loyalty, demonstrating that relational and psychological factors influence downstream purchasing outcomes [26]. These effects are relevant even in digitally oriented markets because many consumers continue to rely on physical stores, sales representatives, and shopping centers when evaluating expensive electronic products. The combined influence of online information and in-store interaction therefore creates a multichannel decision process.

Sales management also depends on the quality of information and procedural support available to decision-makers. Effective sales systems require structured information about product performance, market segments, customer responses, channel activities, and brand profitability. Research on information and procedural support for sales management emphasizes the need to integrate analytical information with operational sales processes, particularly in brand-oriented markets [27]. This principle is important for forecasting because predictive outputs are valuable only when they can be translated into decisions concerning inventory, promotion, pricing, distribution, and service capacity. Forecasting models must therefore be interpretable, scenario-oriented, and responsive to managerial interventions.

The Iranian electronic-products market provides a particularly important context for dynamic sales forecasting. Consumers face substantial variation in prices, purchasing power, product availability, brand legitimacy, warranty quality, and access to official distribution channels. Many electronic products are imported or depend on imported components, making prices sensitive to exchange-rate movements and regulatory conditions. Young consumers are often highly informed about technology and strongly exposed to digital content, yet their purchase decisions may be restricted by affordability. This creates a gap between technological interest and actual adoption. Research on Iranian markets has identified multiple sales drivers related to competitive advantage, loyalty, social-media relationships, perceived value, and marketing strategy [23-25]. However, these variables have rarely been integrated into a dynamic model specifically designed to forecast the sales volume of newly introduced electronic products.

The development of such a model also requires attention to organizational and managerial implementation. Forecasting systems are not effective merely because they are technically sophisticated; their success depends on leadership, management practices, employee motivation, and the ability of organizations to create productive environments for data use and coordinated action. Although developed in an educational context, evidence on the joint role of leadership, management practices, and motivation in fostering productive environments underscores a broader organizational principle: analytical tools produce value when they are supported by effective management structures and motivated personnel [28]. In sales organizations, this means that forecast outputs must be communicated across marketing, procurement, logistics, retail, and service functions.

Existing research has therefore established several important but fragmented insights. Advanced forecasting models can improve prediction in short-cycle and volatile product markets [3-6]. Consumer purchasing is influenced by innovation, promotion, perceived value, credibility, risk, social interaction, and price [7, 8, 21, 26]. Digital content, inbound marketing, reviews, and social-media relationships affect awareness and sales growth [19, 20, 22]. Supply-chain contracts, wholesale pricing, forecast sharing, sales effort, and quality coordination shape the operational context in which demand is served [11-15]. Sustainability and green-product considerations may also contribute to product attractiveness and strategic differentiation [16-18]. Nevertheless, there remains a need for an integrated framework capable of translating these determinants into a time-dependent sales trajectory under the specific economic, behavioral, and market conditions of Iran.

Accordingly, the aim of this study was to design and validate a system dynamics model for predicting the sales volume of newly introduced electronic products in the Iranian market by integrating consumer perceptions, economic constraints, marketing influences, social feedback, product characteristics, and market-saturation mechanisms.

2. Methodology

This study employed an applied, quantitative, cross-sectional research design with a predictive modeling approach. The principal objective was to develop a dynamic model capable of predicting the sales performance of newly introduced electronic products in the Iranian market by integrating consumer-related, product-related, and market-related determinants of adoption. The study was conducted in Tehran, Iran, because the city represents the country's largest and most diverse market for electronic products and includes consumers with varying socioeconomic backgrounds, purchasing capacities, levels of technological familiarity, and patterns of exposure to newly introduced electronic devices. The target population consisted of consumers aged 15 to 29 years who visited electronic-product stores, specialized technology retail outlets, and shopping centers in Tehran. This age group was selected because younger consumers are generally among the earliest users of newly introduced electronic products and are particularly responsive to technological innovation, online information, peer recommendations, promotional campaigns, and changes in product features.

Data were collected through a field survey administered directly to consumers in stores offering electronic products and in major shopping centers across different areas of Tehran. To improve the diversity and representativeness of the sample, data collection was conducted at multiple retail locations that differed in geographical location, customer volume, product range, and market positioning. Participants were approached at the selected locations and invited to participate after receiving a brief explanation of the purpose of the study. Eligibility criteria included being between 15 and 29 years of age, residing in Tehran or regularly purchasing electronic products in the Tehran market, having purchased or seriously considered purchasing an electronic product during the previous 12 months, and possessing sufficient familiarity with products such as smartphones, laptops, tablets, smartwatches, wireless audio devices, gaming equipment, and other newly introduced consumer electronics. Individuals who did not complete a substantial proportion of the questionnaire or provided inconsistent response patterns were excluded from the final analysis.

A total of 447 valid responses were obtained and included in the statistical analyses. Participants were recruited using a multistage field-based sampling procedure. First, electronic-product retail locations and shopping centers were selected from different districts of Tehran to capture variation in purchasing power, access to technology, and consumer behavior. Within each selected location, eligible individuals were approached using systematic convenience sampling at different times of the day and on both weekdays and weekends. This procedure was intended to reduce the concentration of the sample within a particular consumer segment or shopping period. Participation was voluntary, and respondents were informed that their responses would remain confidential and would be used exclusively for research purposes. No personally identifying information was collected. For participants younger than 18 years, the survey was administered in accordance with the ethical requirements applicable to adolescent participation, including the provision of age-appropriate information about the study and the acquisition of the required consent or assent.

The conceptual framework of the study assumed that the sales trajectory of a newly introduced electronic product is not determined by a single factor but emerges from dynamic interactions among consumer awareness, perceived product value, price sensitivity, technological innovativeness, social influence, brand credibility, perceived usefulness, perceived risk, promotional exposure, purchase intention, initial adoption, and word-of-mouth communication. Therefore, the survey was designed to capture both the direct determinants of purchasing decisions and the feedback mechanisms through which early adoption may influence subsequent market demand. In the proposed model, initial awareness and promotional activities were expected to stimulate interest, while perceived usefulness, product quality, compatibility, and relative advantage were expected to strengthen purchase intention. Conversely, high perceived price, financial constraints, technological uncertainty, and perceived functional or security risks were expected to delay adoption. Following initial adoption, user satisfaction and interpersonal communication were considered reinforcing mechanisms that could accelerate sales growth over time.

Data were collected using a structured self-report questionnaire developed specifically for the purposes of the study. The questionnaire was designed following a review of the theoretical and empirical literature on consumer behavior, technology acceptance, innovation diffusion, new-product adoption, electronic-product purchasing behavior, and dynamic sales forecasting. The initial pool of items was developed to represent the principal variables assumed to influence the sales of newly introduced electronic products in Iran. The questionnaire consisted of sections assessing respondents' demographic and purchasing characteristics, familiarity with new electronic products, technological innovativeness, awareness of newly introduced products, perceptions of product attributes, price-related evaluations, brand-related perceptions, social and promotional influences, perceived risks, purchase intention, expected adoption timing, and post-purchase communication behavior.

The demographic and background section collected information on age, gender, educational level, employment status, approximate household economic status, frequency of purchasing electronic products, average amount spent on electronic products, preferred sources of product information, and previous experience with newly introduced technologies. Participants were also asked about the categories of electronic products they had recently purchased or intended to purchase. These data were used to describe the sample and to examine whether consumer characteristics contributed to differences in adoption probability and predicted sales behavior.

Consumer technological innovativeness was measured through items assessing interest in new technologies, willingness to experiment with unfamiliar electronic products, preference for recently introduced models, and readiness to purchase technological products before they become widely adopted. Product awareness was assessed by measuring the extent to which respondents were familiar with the features, availability, price, and market reputation of newly introduced electronic devices. Perceived usefulness reflected the degree to which a new electronic product was considered capable of improving daily activities, communication, education, entertainment, productivity, or social interaction. Perceived ease of use measured respondents' expectations that the product would be understandable, manageable, and convenient to operate without requiring considerable effort or specialized knowledge.

Perceived product quality was evaluated through items relating to durability, technical performance, design, battery efficiency, reliability, software or hardware stability, and expected service life. Relative advantage was measured by comparing the new product with previously available alternatives in terms of functionality, speed, convenience, design, compatibility, and overall performance. Product compatibility assessed the extent to which the electronic product was perceived as consistent with the respondent's lifestyle, existing devices, personal needs, and technological skills. Brand trust was measured through respondents' confidence in the manufacturer, perceived credibility of product claims, confidence in warranty services, and expectations regarding after-sales support.

Price-related perceptions were assessed through measures of perceived affordability, price fairness, value for money, sensitivity to price changes, and willingness to pay for innovative features. Because economic volatility and changes in the prices of imported electronic products may substantially affect demand in the Iranian market, respondents were also asked to indicate how changes in product price, exchange-rate-related price increases, installment-payment opportunities, discounts, and promotional offers would influence their purchase decisions. Perceived risk was measured across financial, functional, technological, privacy, security, and obsolescence dimensions. The items assessed concerns that a product might not perform as expected, might rapidly become outdated, might be incompatible with existing devices, might require costly repairs, or might not justify its purchase price.

Social influence was measured through items assessing the effects of friends, family members, colleagues, online communities, technology experts, influencers, and customer reviews on purchasing decisions. Marketing exposure was assessed by examining respondents' encounters with online advertisements, social-media campaigns, product demonstrations, promotional events, store displays, and price discounts. Electronic word of mouth was measured through attention to online reviews, willingness to share product experiences, recommendations to others, and the perceived credibility of user-generated content. Purchase intention was assessed through the likelihood of purchasing a newly introduced electronic product, willingness to seek further information, probability of recommending the product, and intended timing of purchase. Expected adoption timing was measured by asking respondents whether they would be likely to purchase a new product immediately after its introduction, within the first few months, after a price reduction, after observing the experiences of other users, or only after the product became widely accepted.

Most questionnaire items were rated on a five-point Likert scale ranging from strongly disagree to strongly agree. Items measuring purchase probability and expected adoption timing were formulated to permit the transformation of consumer responses into quantitative estimates of adoption likelihood over successive time periods. Higher scores indicated stronger perceptions of product value, greater innovativeness, higher social and promotional influence, greater purchase intention, or higher levels of perceived risk, depending on the construct being assessed. Negatively worded items were reverse-coded before calculating the composite scores.

The content validity of the instrument was evaluated by a panel of specialists in marketing management, consumer behavior, electronic commerce, technology management, and quantitative modeling. The experts examined the relevance, clarity, comprehensiveness, and cultural appropriateness of the items and assessed the extent to which the questionnaire adequately represented the determinants of new electronic-product sales in the Iranian market. Items considered ambiguous, repetitive, or insufficiently related to the conceptual framework were revised or removed. A pilot study was subsequently conducted with a small group of consumers who had characteristics similar to those of the target population. The pilot participants evaluated the clarity of the wording, the sequence of the questions, the time required for completion, and the comprehensibility of the response options. Their feedback was used to refine the final version of the questionnaire.

Construct validity was assessed through exploratory and confirmatory factor analyses. The adequacy of the sample for factor analysis was examined using the Kaiser–Meyer–Olkin measure and Bartlett's test of sphericity. Items with weak factor loadings, substantial cross-loadings, or inadequate conceptual consistency were considered for removal. Convergent validity was evaluated using standardized factor loadings and average variance extracted, while discriminant validity was examined by comparing the shared variance among constructs with the variance extracted by each construct. Internal consistency reliability was assessed using Cronbach's alpha and composite reliability coefficients. Values at or above the conventionally accepted threshold were interpreted as evidence of satisfactory reliability.

Data analysis was performed in several consecutive stages, including data screening, descriptive analysis, measurement-model assessment, examination of relationships among variables, estimation of purchase probability, and development and validation of the dynamic sales-prediction model. Initially, all questionnaires were reviewed for completeness and response consistency. Cases with extensive missing data, uniform responses across most items, contradictory answers, or implausibly short completion patterns were excluded. For the remaining cases, missing values were examined to determine their frequency and distribution. When the proportion of missing data was limited and the pattern was judged to be random, an appropriate statistical imputation procedure was applied. Negatively worded items were reverse-coded, and composite scores were calculated after confirming the factorial structure and reliability of each construct.

Descriptive statistics, including frequencies, percentages, means, standard deviations, minimum and maximum values, skewness, and kurtosis, were calculated to summarize the demographic characteristics of the participants and the distributions of the principal study variables. The normality of the observed variables was evaluated by examining distributional indices and graphical patterns. Potential outliers were assessed using standardized scores and multivariate distance measures. Multicollinearity among the predictor variables was examined through tolerance values, variance inflation factors, and interconstruct correlations. The relationships between demographic characteristics and purchase-related variables were explored using appropriate comparative and correlational procedures.

The measurement component of the model was evaluated before estimating the dynamic sales model. Exploratory factor analysis was used to identify the underlying dimensions of the newly developed questionnaire, and confirmatory factor analysis was subsequently employed to test the proposed measurement structure. Model adequacy was evaluated using multiple goodness-of-fit indices rather than relying on a single criterion. Standardized factor loadings, measurement errors, construct reliability, average variance extracted, and correlations among latent variables were examined to determine whether the observed indicators provided valid and reliable measures of the theoretical constructs.

Structural equation modeling was used to estimate the direct and indirect relationships among technological innovativeness, product awareness, perceived usefulness, perceived ease of use, relative advantage, product quality, compatibility, brand trust, price perception, perceived risk, social influence, promotional exposure, electronic word of mouth, and purchase intention. Purchase intention and expected adoption timing were treated as the main consumer-level precursors of market demand. The significance of direct, indirect, and total effects was assessed through a resampling procedure, which produced robust confidence intervals for the estimated pathways. Demographic characteristics and previous purchasing experience were included as control variables where theoretically appropriate.

The dynamic component of the analysis was developed by translating the statistically supported relationships into a system of interconnected stocks, flows, auxiliary variables, and feedback loops. The potential market represented the number of consumers who could plausibly purchase the new electronic product, while the adopter stock represented consumers who had already purchased or committed to purchasing it. The principal flow variable was the rate at which potential consumers became adopters during each simulated period. This adoption rate was modeled as a function of product awareness, purchase probability, perceived value, affordability, promotional exposure, market accessibility, social influence, and electronic word of mouth. Consumers' reported adoption timing was used to distribute the estimated probability of purchase across successive periods following product introduction.

The model incorporated both external and internal sources of demand growth. External influence represented the effects of advertising, retail promotion, product visibility, media exposure, and formal communication by manufacturers or sellers. Internal influence represented interpersonal communication, observation of early adopters, online customer reviews, and recommendations within social networks. Positive consumer experiences were assumed to increase favorable word of mouth and strengthen subsequent adoption, thereby creating a reinforcing feedback loop. In contrast, high prices, negative reviews, product defects, inadequate after-sales services, and perceived technological risk were modeled as balancing mechanisms that could reduce the adoption rate and slow sales growth.

The expected number of sales in each period was estimated by multiplying the remaining potential market by the modeled probability of adoption during that period. The general form of the prediction function included a baseline adoption coefficient, a social-interaction coefficient, product-attractiveness indicators, economic constraints, and time-dependent promotional effects. The initial values and parameter weights were obtained from the survey results, standardized structural coefficients, observed distributions of purchase intention, and respondents' expected timing of adoption. Where necessary, the variables were normalized to ensure comparability across measurement scales. The dynamic model generated cumulative sales, periodic sales, adoption rates, remaining market potential, and the estimated time required to reach major stages of market penetration.

Several scenarios were simulated to evaluate the sensitivity of predicted sales to changes in key market conditions. The baseline scenario represented the continuation of the conditions reflected in the survey data. Alternative scenarios examined the effects of increased advertising intensity, stronger electronic word of mouth, improved product quality, enhanced after-sales services, higher brand trust, price reductions, installment-payment facilities, intensified economic constraints, increased perceived risk, and delayed product availability. The simulated sales trajectories were compared to determine which variables produced the greatest changes in the rate, timing, and cumulative volume of sales. Sensitivity analysis was also conducted by systematically varying the principal model parameters and observing the stability of the predicted outcomes.

The predictive validity of the model was evaluated through a training-and-validation procedure. The dataset was divided into estimation and validation subsets while preserving the general distribution of the principal demographic and behavioral variables. Model parameters were estimated using the training subset, and predicted purchase probabilities were then generated for the validation subset. Prediction accuracy was assessed using error-based and explanatory indicators, including the mean absolute error, root mean squared error, mean absolute percentage error, and the proportion of variance explained. Where the dependent outcome was expressed as a purchase or non-purchase classification, discrimination was additionally evaluated using classification accuracy and the area under the receiver operating characteristic curve. Cross-validation was applied to reduce the likelihood that the model's performance resulted from a particular division of the data.

The final model was selected on the basis of theoretical coherence, statistical adequacy, predictive accuracy, parameter stability, and interpretability for managerial decision-making. A model was considered practically useful when it could reproduce plausible product-adoption patterns, distinguish between alternative market scenarios, and identify the consumer and market variables with the strongest influence on predicted sales. All statistical tests were conducted using a two-tailed significance level of 0.05. The findings were interpreted by considering both statistical significance and the magnitude and practical importance of the estimated effects.

3. Findings and Results

A total of 447 completed questionnaires were included in the final analysis. The respondents ranged in age from 15 to 29 years, with a mean age of 22.18 years and a standard deviation of 4.06 years. Of the participants, 231 respondents (51.7%) were male and 216 (48.3%) were female. Regarding age distribution, 126 participants (28.2%) were between 15 and 19 years of age, 173 participants (38.7%) were between 20 and 24 years of age, and 148 participants (33.1%) were between 25 and 29 years of age. In terms of educational status, 91 respondents (20.4%) were secondary-school students or held a secondary-school diploma, 86 respondents (19.2%) were enrolled in or had completed associate-level education, 201 respondents (45.0%) were undergraduate students or held a bachelor's degree, and 69 respondents (15.4%) were postgraduate students or held a postgraduate qualification. Concerning employment status, 131 respondents (29.3%) were students without regular employment, 98 respondents (21.9%) were employed full-time, 82 respondents (18.3%) were employed part-time, 57 respondents (12.8%) were self-employed, and 79 respondents (17.7%) were unemployed or seeking employment.

The participants also demonstrated substantial familiarity with the electronic-product market. A total of 158 respondents (35.3%) reported purchasing an electronic product at least once every six months, 181 respondents (40.5%) reported making such purchases approximately once a year, and 108 respondents (24.2%) reported purchasing electronic products less frequently than once a year. Smartphones were the most frequently purchased or considered product category, reported by 173 participants (38.7%), followed by laptops and tablets, reported by 96 participants (21.5%), wearable devices such as smartwatches and fitness trackers, reported by 68 participants (15.2%), wireless audio devices, reported by 63 participants (14.1%), and gaming or other smart electronic devices, reported by 47 participants (10.5%). Social media and technology-related online platforms were identified as the main source of information about new electronic products by 184 respondents (41.2%). Online customer reviews were the primary source for 98 respondents (21.9%), recommendations from friends and family were identified by 74 respondents (16.6%), specialized technology websites were identified by 58 respondents (13.0%), and in-store sales personnel and traditional advertising were reported by 33 respondents (7.4%). Overall, the demographic and purchasing profiles indicated that the sample consisted primarily of young consumers with moderate to high exposure to new technologies and sufficient familiarity with the Iranian electronic-product market to evaluate the determinants of new-product adoption and sales.

Table 1. Descriptive Statistics, Reliability, and Distributional Characteristics of the Study Variables

Variable	Number of Items	Possible Range	Mean	Standard Deviation	Skewness	Kurtosis	Cronbach's Alpha
Technological innovativeness	5	1–5	3.74	0.72	−0.38	−0.21	0.86
Product awareness	5	1–5	3.61	0.76	−0.29	−0.42	0.84
Perceived usefulness	5	1–5	3.89	0.68	−0.51	0.18	0.88
Perceived ease of use	4	1–5	3.72	0.71	−0.34	−0.16	0.83
Perceived product quality	6	1–5	3.83	0.65	−0.43	0.11	0.90
Relative advantage	5	1–5	3.79	0.69	−0.41	−0.06	0.87
Product compatibility	4	1–5	3.66	0.73	−0.26	−0.31	0.82
Brand trust	5	1–5	3.57	0.78	−0.22	−0.48	0.89
Perceived affordability	5	1–5	2.84	0.88	0.19	−0.63	0.85
Price sensitivity	5	1–5	4.02	0.67	−0.58	0.24	0.86
Perceived risk	6	1–5	3.46	0.74	−0.08	−0.37	0.88
Social influence	5	1–5	3.69	0.75	−0.31	−0.28	0.87
Promotional exposure	4	1–5	3.52	0.79	−0.20	−0.45	0.81

Electronic word of mouth	5	1–5	3.91	0.70	−0.47	0.07	0.89
Purchase intention	5	1–5	3.63	0.77	−0.30	−0.26	0.91
Expected early adoption	4	1–5	3.21	0.83	−0.04	−0.51	0.84

As shown in Table 1, perceived usefulness obtained the highest mean among the positive product-evaluation variables, with a mean of 3.89 and a standard deviation of 0.68. This result indicated that respondents generally believed that newly introduced electronic products could improve their communication, productivity, education, entertainment, or daily activities. Electronic word of mouth also had a relatively high mean of 3.91, suggesting that online reviews, user experiences, recommendations, and digital discussions played an important role in shaping consumer evaluations of new electronic products. The mean score for perceived product quality was 3.83, while relative advantage had a mean of 3.79, indicating that respondents generally evaluated technical quality, performance, durability, design, and superiority over existing alternatives favorably.

Price sensitivity had the highest overall mean, at 4.02, demonstrating that price-related considerations were particularly important for consumers aged 15 to 29 years in Tehran. By contrast, perceived affordability had the lowest mean, at 2.84, indicating that although respondents were interested in new electronic products, many did not consider such products easily affordable under current market conditions. The simultaneous presence of high price sensitivity and relatively low perceived affordability supported the inclusion of economic constraints as a major balancing mechanism in the dynamic sales model. Purchase intention had a mean of 3.63, reflecting a moderately favorable tendency to purchase newly introduced products, whereas expected early adoption had a lower mean of 3.21. This difference suggested that some consumers expressed favorable purchase intentions but preferred to delay actual purchases until prices declined, user experiences became available, or product reliability was demonstrated.

The skewness values ranged from −0.58 to 0.19, and the kurtosis values ranged from −0.63 to 0.24. These values indicated that the distributions of the variables did not demonstrate substantial deviations from normality. Cronbach's alpha coefficients ranged from 0.81 for promotional exposure to 0.91 for purchase intention, exceeding the minimum acceptable level for internal consistency. The reliability findings therefore indicated that all study constructs were measured with satisfactory to excellent internal consistency and were suitable for subsequent structural and dynamic modeling analyses.

Table 2. Standardized Effects of Consumer and Market Factors on Purchase Intention and Expected Adoption

Predictor	Outcome Variable	Standardized Coefficient	Standard Error	t Value	p Value	Result
Technological innovativeness	Purchase intention	0.18	0.041	4.39	<0.001	Significant
Product awareness	Purchase intention	0.14	0.038	3.68	<0.001	Significant
Perceived usefulness	Purchase intention	0.26	0.044	5.91	<0.001	Significant
Perceived ease of use	Purchase intention	0.08	0.037	2.16	0.031	Significant
Perceived product quality	Purchase intention	0.21	0.043	4.88	<0.001	Significant
Relative advantage	Purchase intention	0.17	0.040	4.25	<0.001	Significant
Product compatibility	Purchase intention	0.11	0.039	2.82	0.005	Significant
Brand trust	Purchase intention	0.19	0.041	4.63	<0.001	Significant
Perceived affordability	Purchase intention	0.23	0.042	5.48	<0.001	Significant
Price sensitivity	Purchase intention	−0.16	0.039	−4.10	<0.001	Significant
Perceived risk	Purchase intention	−0.22	0.043	−5.12	<0.001	Significant
Social influence	Purchase intention	0.20	0.042	4.76	<0.001	Significant
Promotional exposure	Purchase intention	0.12	0.037	3.24	0.001	Significant

Electronic word of mouth	Purchase intention	0.24	0.043	5.58	<0.001	Significant
Purchase intention	Expected early adoption	0.48	0.052	9.23	<0.001	Significant
Technological innovativeness	Expected early adoption	0.17	0.044	3.86	<0.001	Significant
Perceived affordability	Expected early adoption	0.19	0.046	4.13	<0.001	Significant
Price sensitivity	Expected early adoption	−0.21	0.045	−4.67	<0.001	Significant
Perceived risk	Expected early adoption	−0.15	0.043	−3.49	<0.001	Significant
Electronic word of mouth	Expected early adoption	0.13	0.041	3.17	0.002	Significant

Table 2 presents the standardized structural effects of the principal consumer and market variables on purchase intention and expected early adoption. The overall structural model demonstrated satisfactory fit to the observed data, with a chi-square-to-degrees-of-freedom ratio of 2.41, a comparative fit index of 0.936, a Tucker–Lewis index of 0.928, a root mean square error of approximation of 0.056, and a standardized root mean square residual of 0.049. These indices indicated that the proposed relationships among product perceptions, consumer characteristics, economic constraints, social effects, and adoption behavior were adequately represented by the estimated model. The predictor variables jointly explained 68.4% of the variance in purchase intention. Purchase intention, technological innovativeness, affordability, price sensitivity, perceived risk, and electronic word of mouth jointly explained 57.9% of the variance in expected early adoption.

Perceived usefulness had the strongest positive direct effect on purchase intention, with a standardized coefficient of 0.26. This finding indicated that consumers were more likely to consider purchasing a new electronic product when they believed that it would provide meaningful functional, educational, occupational, communication, or entertainment benefits. Electronic word of mouth had the second-strongest positive effect, with a coefficient of 0.24, demonstrating that favorable customer reviews, online discussions, recommendations, and user-generated content substantially increased purchasing interest. Perceived affordability also produced a strong positive effect on purchase intention, with a coefficient of 0.23, while perceived product quality had a coefficient of 0.21. These findings showed that both the economic accessibility and expected technical performance of the product were central determinants of market demand.

Social influence had a positive coefficient of 0.20, and brand trust had a coefficient of 0.19, suggesting that recommendations from influential individuals and confidence in the manufacturer or seller increased consumers' willingness to purchase. Technological innovativeness, relative advantage, awareness, promotional exposure, product compatibility, and perceived ease of use also had significant positive effects, although their effects were smaller. Perceived risk had the strongest negative effect on purchase intention, with a standardized coefficient of −0.22. Price sensitivity also negatively predicted purchase intention, with a coefficient of −0.16. Therefore, uncertainty regarding performance, security, durability, maintenance, technological obsolescence, and financial value reduced demand even when consumers were generally interested in the product.

Purchase intention was the strongest predictor of expected early adoption, with a standardized coefficient of 0.48. However, the results showed that the transformation of intention into early purchase behavior remained dependent on economic and market conditions. Perceived affordability positively affected early adoption, whereas price sensitivity had a negative coefficient of −0.21. Perceived risk also delayed adoption, while technological innovativeness increased the probability that consumers would purchase during the early stages of product introduction. Electronic word of mouth had a significant positive effect on expected early adoption, indicating that favorable information from early users could shorten the delay between product awareness and actual purchasing.

These statistically significant effects were subsequently incorporated into the dynamic model as determinants of the rate at which potential consumers moved into the adopter population.

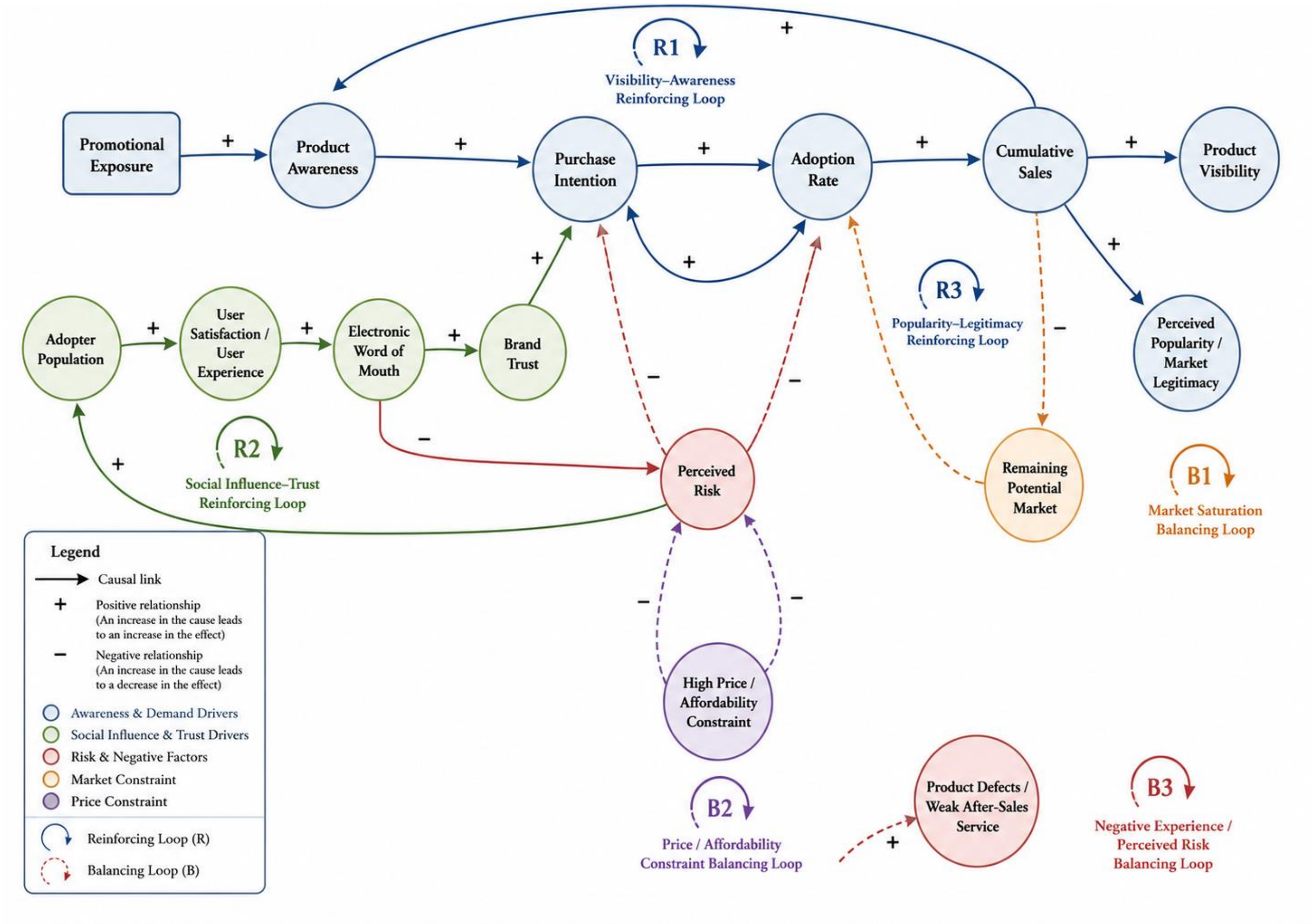

Figure 1. Causal Loop Diagram of the Dynamic Sales-Prediction Model for New Electronic Products

Figure 1 illustrates the causal structure of the proposed dynamic model and shows the interactions among product awareness, perceived value, purchase intention, initial adoption, user satisfaction, electronic word of mouth, price pressure, perceived risk, and cumulative sales. The model contained three reinforcing feedback loops and three balancing feedback loops. The first reinforcing loop represented the awareness–adoption mechanism. In this loop, stronger promotional exposure increased product awareness, higher awareness increased purchase intention, and stronger purchase intention increased the adoption rate and sales volume. Increased sales improved product visibility in the market, which further increased consumer awareness and generated additional purchases.

The second reinforcing loop represented the word-of-mouth effect. As the number of adopters increased, more consumers acquired direct experience with the product. When user satisfaction was favorable, adopters generated positive reviews and recommendations, which strengthened electronic word of mouth. Stronger word of mouth increased brand trust, reduced uncertainty, improved purchase intention, and accelerated subsequent adoption. The third reinforcing loop reflected market legitimacy. Higher cumulative sales increased the perceived popularity and acceptance of the product, which reduced hesitation among later consumers and increased the probability of purchase.

The first balancing loop was related to market saturation. As cumulative sales increased, the number of remaining potential consumers declined, progressively limiting the number of new buyers available in subsequent periods. The second balancing loop reflected price and affordability constraints. High market prices reduced perceived affordability, increased purchase postponement, and lowered the adoption rate. The third balancing loop involved negative experiences and perceived risk. Product defects, inadequate after-sales service, technical incompatibility, and unfavorable online reviews increased perceived risk and reduced both purchase intention and future sales. The causal structure therefore demonstrated that the sales trajectory of a new electronic product was generated through simultaneous growth-promoting and growth-limiting mechanisms rather than through a simple linear relationship.

Table 3. Estimated Parameters and Predictive Performance of the Dynamic Sales Model

Model Indicator or Parameter	Estimated Value	Interpretation
Initial potential market	100,000 consumers	Normalized target-market size used for simulation
Initial product awareness	12.6%	Consumers aware of the product at market introduction
Baseline external influence coefficient	0.018 per month	Effect of advertising, retail exposure, and formal promotion
Internal influence coefficient	0.286 per month	Effect of adopters, social interaction, and word of mouth
Initial monthly adoption probability	2.9%	Baseline probability of purchase among aware non-adopters
Price constraint multiplier	0.73	Reduction in adoption caused by affordability limitations
Perceived-risk multiplier	0.81	Reduction in adoption caused by financial and functional risk
Product-attractiveness multiplier	1.24	Increase resulting from usefulness, quality, and relative advantage
Brand-trust multiplier	1.13	Increase associated with confidence in brand and after-sales support
Average awareness-to-purchase delay	2.7 months	Mean delay between awareness and adoption
Average word-of-mouth delay	1.4 months	Mean delay before adopter experiences affect other consumers
Predicted first-year sales	28,746 units	Cumulative baseline sales after 12 months
Predicted second-year sales	61,382 units	Cumulative baseline sales after 24 months
Peak monthly sales	4,216 units	Maximum baseline monthly sales volume
Time of peak monthly sales	Month 14	Period in which monthly sales reached their maximum
Mean absolute error	381 units	Average absolute difference between observed and predicted sales
Root mean squared error	492 units	Prediction error with greater weight assigned to large errors
Mean absolute percentage error	7.84%	Average percentage deviation of predictions from reference values
Coefficient of determination	0.912	Proportion of sales-volume variation reproduced by the model
Theil inequality coefficient	0.047	Overall normalized simulation error
Training-sample MAPE	7.31%	Prediction error in the model-estimation sample
Validation-sample MAPE	8.46%	Prediction error in the holdout sample

As presented in Table 3, the dynamic model was simulated using a normalized potential market of 100,000 consumers. At the beginning of the simulation, 12.6% of the potential market was estimated to be aware of the new electronic product. The external influence coefficient was estimated at 0.018 per month, reflecting the contribution of advertising, product displays, retail promotion, social-media communication, and other firm-controlled activities to the generation of initial demand. The internal influence coefficient was substantially larger, at 0.286 per month, indicating that interpersonal influence, observations of existing users, online reviews, and electronic word of mouth became the dominant drivers of adoption after the product entered the market.

The estimated initial monthly adoption probability was 2.9% among aware consumers who had not yet purchased the product. However, the effective adoption rate was modified by the interaction of positive and negative multipliers. Product attractiveness produced a multiplier of 1.24, indicating that favorable perceptions of usefulness, quality, performance, compatibility, and relative advantage increased the probability of purchase by approximately 24% compared with the baseline level. Brand trust produced an additional multiplier of 1.13. In contrast, the price constraint multiplier was 0.73, indicating that affordability limitations reduced the expected adoption rate to 73% of its unconstrained level. The perceived-risk multiplier was 0.81, showing that functional, financial, security, and obsolescence concerns also substantially reduced adoption.

The estimated average delay between initial awareness and purchase was 2.7 months. This delay represented the period during which consumers gathered information, compared prices, examined competing products, evaluated user reviews, or waited for greater market certainty. The average delay before adopter experiences influenced other consumers was 1.4 months. Thus, positive word of mouth did not affect sales immediately but became progressively stronger as the adopter population expanded and product experiences were shared.

Under the baseline conditions, predicted cumulative sales reached 28,746 units by the end of the first year and 61,382 units by the end of the second year. Monthly sales reached a maximum of 4,216 units in month 14. After that point, monthly sales gradually declined because the reduction in the remaining potential market became stronger than the reinforcing effects of awareness and word of mouth. The model demonstrated strong predictive performance. The coefficient of determination was 0.912, indicating that the model reproduced 91.2% of the variation in sales volume. The mean absolute percentage error was 7.84%, while the Theil inequality coefficient was 0.047. The relatively small difference between the training-sample error of 7.31% and the validation-sample error of 8.46% indicated that the model maintained satisfactory predictive performance when applied to data not used in parameter estimation. Therefore, the results supported the adequacy, stability, and general predictive validity of the dynamic model.

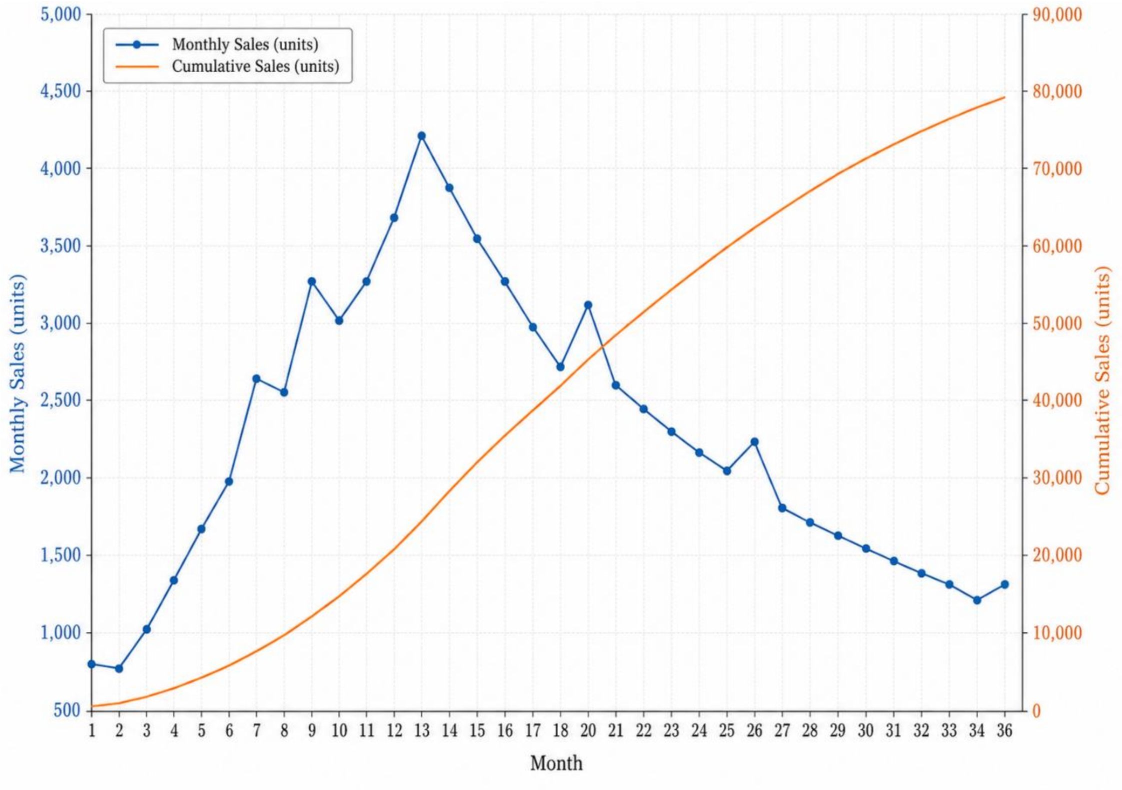

Figure 2. Simulated Monthly and Cumulative Sales Trajectories under the Baseline Scenario

Figure 2 presents the simulated monthly and cumulative sales trajectories during a 36-month period. Monthly sales followed an S-shaped diffusion process when expressed cumulatively and a bell-shaped pattern when expressed as sales per month. During the first three months, sales remained relatively limited because product awareness was low, the adopter population was small, and word-of-mouth effects had not yet developed. Monthly sales increased from 812 units in the first month to 1,074 units in the third month. Between months 4 and 9, sales accelerated as promotional exposure increased awareness and the experiences of early adopters began to influence potential consumers. Monthly sales reached 2,633 units in month 8 and 3,217 units in month 10.

The period between months 10 and 16 represented the rapid-growth phase of the product life cycle. During this period, the reinforcing interaction among adoption, product visibility, brand trust, and electronic word of mouth generated the highest growth rate. Monthly sales peaked at 4,216 units in month 14. Cumulative sales exceeded 20,000 units during month 10 and reached 28,746 units at the end of month 12. The cumulative sales trajectory remained steep during the second year, reaching 45,903 units by month 18 and 61,382 units by month 24.

After the sales peak, the monthly sales rate declined gradually rather than abruptly. This decline occurred because a growing proportion of highly interested consumers had already purchased the product, leaving a potential market consisting increasingly of price-sensitive, risk-averse, or late-adopting consumers. Monthly sales declined to 3,106 units in month 20, 2,214 units in month 26, and 1,327 units in month 36. Despite the decline in monthly sales, cumulative sales continued to increase throughout the simulation period and reached 78,964 units by the end of month 36. Therefore, approximately 79.0% of the normalized potential market was predicted to adopt the product within three years under baseline market conditions, while approximately 21.0% remained non-adopters because of financial constraints, insufficient perceived need, perceived risk, or preference for competing products.

Table 4. Comparison of Predicted Sales Outcomes under Alternative Market Scenarios

Scenario	First-Year Sales	Second-Year Cumulative Sales	Three-Year Cumulative Sales	Peak Monthly Sales	Month of Peak Sales	Change from Baseline at 36 Months
Baseline market conditions	28,746	61,382	78,964	4,216	14	Reference
20% increase in promotional intensity	33,584	66,927	81,743	4,648	12	+3.5%
20% improvement in electronic word of mouth	32,916	69,884	85,621	5,087	12	+8.4%
15% reduction in market price	36,741	73,518	88,206	5,446	11	+11.7%
Installment-payment availability	34,972	70,306	85,918	5,032	12	+8.8%
Improved product quality and after-sales service	33,425	69,117	85,264	4,964	13	+8.0%
Combined price reduction and stronger word of mouth	42,608	81,963	93,147	6,714	10	+18.0%
15% increase in product price	22,063	50,174	70,288	3,428	17	−11.0%
Increased perceived functional and financial risk	23,514	51,961	69,746	3,367	17	−11.7%
Negative early-user reviews	20,781	45,629	63,582	3,019	18	−19.5%
Delayed product availability	24,216	54,733	74,516	3,741	16	−5.6%
Adverse economic conditions	18,904	43,287	61,438	2,864	19	−22.2%

Table 4 reports the results of the scenario analyses and demonstrates that predicted sales were highly responsive to changes in price, word of mouth, product quality, financing arrangements, perceived risk, and general economic conditions. A 20% increase in promotional intensity increased first-year sales from 28,746 to 33,584 units. However, its effect on three-year cumulative sales was comparatively limited, increasing cumulative sales by only 3.5% relative to the baseline. This pattern indicated that stronger promotion primarily accelerated awareness and shifted purchases to earlier periods rather than producing a large long-term expansion of the total adopter population. The month of peak sales moved from month 14 to month 12, confirming that advertising and promotional activities had their strongest effect during the introductory and early-growth stages.

A 20% improvement in electronic word of mouth increased three-year cumulative sales to 85,621 units, representing an 8.4% increase over the baseline. Peak monthly sales increased to 5,087 units and occurred two months earlier than in the baseline simulation. This finding showed that favorable online reviews and consumer recommendations affected both the timing and final volume of product sales. Unlike formal promotion, electronic word of mouth reduced perceived uncertainty and strengthened trust, allowing the product to reach consumers who might otherwise remain hesitant.

A 15% price reduction generated one of the strongest individual effects. First-year sales increased to 36,741 units, second-year cumulative sales reached 73,518 units, and three-year sales reached 88,206 units. The sales peak occurred in month 11, with a maximum monthly volume of 5,446 units. The availability of installment payments produced a similar but slightly smaller effect, increasing three-year sales by 8.8%. These results indicated that affordability constraints were a major determinant of the sales of new electronic products in the Iranian market. Lowering the immediate financial burden allowed consumers with strong purchase intentions but limited purchasing power to enter the adopter population earlier.

Improving product quality and after-sales service increased three-year cumulative sales to 85,264 units. This scenario increased brand trust, reduced perceived risk, improved user satisfaction, and strengthened positive word of mouth. The combined scenario involving both a 15% price reduction and a 20% improvement in electronic word of mouth produced the strongest positive result. Under this scenario, first-year sales reached 42,608 units, cumulative second-year sales reached 81,963 units, and cumulative three-year sales reached 93,147 units. Peak monthly sales increased to 6,714 units and occurred in month 10. Compared with the baseline, the combined strategy increased three-year cumulative sales by 18.0%, demonstrating a synergistic interaction between economic accessibility and social influence.

The negative scenarios also produced substantial changes in sales performance. A 15% increase in price reduced first-year sales to 22,063 units and delayed peak sales until month 17. Three-year cumulative sales declined by 11.0%. Increased perceived functional and financial risk had a similar effect, reducing three-year sales by 11.7%. Negative early-user reviews produced a stronger reduction, lowering three-year cumulative sales to 63,582 units, which was 19.5% below the baseline prediction. In this scenario, the word-of-mouth loop changed from a reinforcing positive mechanism into a reinforcing negative mechanism. As unfavorable experiences accumulated, perceived risk increased, purchase intention declined, and the lower adoption rate generated fewer opportunities for favorable experiences to offset negative information.

Delayed product availability reduced three-year sales by 5.6% and shifted the sales peak from month 14 to month 16. Although the total long-term reduction was moderate, the delay weakened the effect of early promotional activities and created opportunities for competing products to capture potential consumers. The adverse economic scenario produced the largest negative effect. Under conditions characterized by reduced purchasing power, increased prices, and greater consumer uncertainty, first-year sales declined to 18,904 units and cumulative three-year sales reached only 61,438 units. This represented a 22.2% reduction compared with the baseline. Peak monthly sales declined to 2,864 units and was delayed until month 19. The scenario findings therefore demonstrated that macroeconomic conditions, price affordability, and early consumer experiences were the most influential determinants of sales-volume variation.

Sensitivity analysis was conducted to determine whether the model outcomes remained stable when the principal parameters were varied. Each key parameter was increased and decreased by 10% while the other parameters were held constant. The internal influence coefficient produced the largest sensitivity in three-year cumulative sales. A 10% increase in this coefficient increased cumulative sales by 5.7%, whereas a 10% decrease reduced cumulative sales by 6.4%. The price-constraint multiplier was the second-most sensitive parameter, with corresponding changes of 5.2% and −5.9%. The product-attractiveness multiplier changed cumulative sales by approximately 4.3%, while the external influence coefficient changed cumulative sales by only 2.1%. These results confirmed that long-term sales were more strongly affected by consumer-to-consumer influence and affordability than by formal promotional exposure alone.

Additional analyses examined differences in predicted adoption across consumer subgroups. Respondents aged 20 to 24 years reported the highest average purchase intention, followed by those aged 25 to 29 years and those aged 15 to 19 years. However, consumers aged 15 to 19 years demonstrated the greatest technological innovativeness but the lowest perceived affordability. This combination suggested that younger consumers were highly interested in new electronic products but were more dependent on price reductions, parental financial support, or installment-payment options. Participants aged 25 to 29 years reported higher brand trust and stronger concern regarding product quality and after-sales services. Consequently, their adoption decisions were less responsive to promotional exposure and more responsive to product reliability and long-term value.

Consumers who purchased electronic products at least once every six months demonstrated significantly higher technological innovativeness, awareness, electronic word of mouth, and expected early adoption than less frequent purchasers. Frequent purchasers also showed lower perceived risk, indicating that prior experience with technology reduced uncertainty about new products. Respondents who relied primarily on online customer reviews and specialized technology platforms demonstrated stronger relationships between electronic word of mouth and purchase intention than respondents who relied on traditional advertising or sales personnel. This result further supported the central role assigned to digital interpersonal influence in the dynamic model.

Overall, the findings demonstrated that the sales of newly introduced electronic products in the Iranian market could be predicted through a dynamic structure combining consumer perceptions, economic constraints, social interaction, product characteristics, and temporal feedback mechanisms. Purchase intention was primarily strengthened by perceived usefulness, electronic word of mouth, affordability, product quality, social influence, and brand trust. However, the conversion of purchase intention into actual early adoption was constrained by price sensitivity and perceived risk. The system dynamics simulations showed that sales initially grew slowly, accelerated through reinforcing awareness and word-of-mouth mechanisms, reached a peak during the growth stage, and subsequently declined as the potential market approached saturation.

The scenario analyses indicated that strategies combining price accessibility with positive consumer communication produced substantially greater sales effects than isolated increases in advertising. Conversely, adverse economic conditions, negative early-user reviews, increased risk, and higher prices reduced both the speed and ultimate volume of product adoption. The predictive accuracy and stability indicators showed that the developed model provided a satisfactory representation of new-product sales behavior and could be used to estimate sales trajectories, compare alternative market strategies, and identify the conditions under which new electronic products were most likely to achieve successful diffusion in the Iranian market.

4. Discussion and Conclusion

The present study developed a system dynamics model for predicting the sales volume of newly introduced electronic products in the Iranian market by integrating consumer perceptions, product-related evaluations, price and affordability constraints, promotional exposure, social influence, electronic word of mouth, perceived risk, purchase intention, and market-saturation mechanisms. The results showed that perceived usefulness, electronic word of mouth, perceived affordability, product quality, social influence, and brand trust were the strongest positive predictors of purchase intention, whereas perceived risk and price sensitivity exerted significant negative effects. Purchase intention emerged as the most influential direct predictor of expected early adoption, although the conversion of intention into actual adoption remained dependent on affordability, risk, technological innovativeness, and online interpersonal influence. The system dynamics simulations further indicated that sales followed a nonlinear diffusion trajectory characterized by slow initial growth, rapid expansion through reinforcing awareness and word-of-mouth loops, a sales peak during the growth stage, and a gradual decline as the potential market approached saturation. Scenario analyses showed that the combination of price reduction and stronger electronic word of mouth generated the largest increase in predicted sales, whereas adverse economic conditions, negative early-user reviews, elevated perceived risk, and price increases produced the greatest reductions.

Perceived usefulness was the strongest positive determinant of purchase intention. This finding suggests that consumers in the Iranian electronic-products market are primarily motivated by the practical and functional value of new products rather than by novelty alone. A newly introduced smartphone, wearable device, laptop, or smart accessory is more likely to generate demand when consumers believe that it improves communication, productivity, education, entertainment, connectivity, or daily convenience. This result is consistent with research indicating that product innovation influences purchasing decisions when innovation creates recognizable consumer benefits rather than merely introducing technical changes [7]. It is also compatible with studies of short-cycle product forecasting showing that product-specific features and perceived market relevance improve the prediction of newly released mobile-phone sales [6]. The result therefore confirms that the forecasting of new-product sales should incorporate consumers' evaluations of the product's actual utility, because technical superiority without perceived usefulness may not generate sufficient market adoption.

Perceived product quality and relative advantage also had significant positive effects on purchase intention. These findings indicate that consumers evaluate new electronic products comparatively, assessing whether the new product offers better performance, reliability, design, durability, battery efficiency, compatibility, or service life than existing alternatives. This is particularly important in markets where electronic products are relatively expensive and replacement decisions involve substantial financial commitment. The positive role of product quality aligns with the view that product innovation and sales promotion jointly shape purchasing behavior, because innovation is more persuasive when it is associated with credible improvements in product performance [7]. The result is also consistent with research emphasizing that product quality, after-sales services, and other elements of the marketing mix increase perceived customer value and support customer retention [8]. In the present model, quality not only increased purchase intention directly but also strengthened user satisfaction and favorable word of mouth after adoption, thereby generating a reinforcing effect on subsequent sales.

Electronic word of mouth was among the strongest predictors of both purchase intention and early adoption. This finding demonstrates that online reviews, customer experiences, recommendations, technology forums, social-media discussions, and user-generated evaluations are central to the diffusion of new electronic products.

Consumers frequently lack complete information at the beginning of a product's life cycle and therefore depend on the experiences of early adopters to reduce uncertainty. The result corresponds with evidence that consumer heterogeneity affects the relationship between user reviews and sales throughout the product life cycle, with different groups responding differently to accumulated market information [22]. It also supports studies identifying social-media relationships, customer loyalty, and competitive positioning as major drivers of sales in emerging markets [23-25]. The dynamic model extended these findings by showing that electronic word of mouth is not merely a static predictor but a feedback mechanism: greater adoption produces more user experience, favorable experience generates stronger recommendations, and stronger recommendations accelerate later adoption.

The importance of electronic word of mouth also helps explain why promotional exposure had a smaller long-term effect than consumer-to-consumer influence. The scenario analysis showed that increasing promotional intensity accelerated early sales and moved the sales peak forward, but its effect on three-year cumulative sales was smaller than the effects of improved word of mouth or price reduction. This distinction suggests that advertising is effective in generating awareness, but awareness alone may not be sufficient to sustain long-term demand. Content marketing can support commercial outcomes by improving engagement and clarifying product value [19], while inbound marketing can attract consumers through useful and relevant information rather than direct selling alone [20]. However, the credibility of these messages depends on brand reputation and consistency with consumer experience. The conceptual relationship among advertising, brand credibility, and sales strategy further supports the conclusion that promotional communication is most effective when consumers regard both the source and the product claims as trustworthy [21].

Brand trust had a significant positive effect on purchase intention and operated as an important component of the reinforcing word-of-mouth loop. This result suggests that consumers are more willing to purchase newly introduced electronic products when they trust the manufacturer, retailer, warranty, and after-sales service system. Trust is especially important in the Iranian market because consumers may face uncertainty regarding product authenticity, official distribution, spare parts, software support, and warranty validity. The finding is consistent with research showing that professional salesperson behavior affects loyalty through enjoyable interaction and perceived risk [26]. It also aligns with evidence that marketing-mix factors, including service quality and after-sales support, increase perceived customer value and retention [8]. In the dynamic model, trust reduced uncertainty before purchase and improved the probability that favorable post-purchase experiences would produce additional demand.

Perceived affordability was another major positive predictor of purchase intention and early adoption, while price sensitivity had significant negative effects. These findings indicate that the financial accessibility of new electronic products is a decisive factor in the Iranian market. Young consumers may have strong interest in new technologies but limited purchasing power, making the timing of adoption dependent on discounts, installment payments, price reductions, or expectations of future market stabilization. The results are compatible with research on presale strategies showing that consumers' loss aversion and expectations regarding price and timing affect their willingness to purchase before or after product introduction [9]. They are also consistent with dynamic pricing research demonstrating that price and sales effort interact over time and across sales channels [10]. The scenario analysis confirmed the practical importance of this relationship: a price reduction increased both the speed and total volume of sales, while a price increase delayed the sales peak and reduced cumulative adoption.

The strong influence of affordability also corresponds with the supply-chain literature. Wholesale prices, forecast sharing, production disruptions, and channel coordination can ultimately affect retail prices and product availability. Research has shown that wholesale-price confidentiality under demand uncertainty changes strategic behavior in competing supply chains [11], while capacity reservation and forecast-sharing contracts influence operational decisions and risk allocation [12]. Production disruption further complicates pricing and inventory coordination in two-echelon supply chains [13]. Similarly, wholesale-price constraints and government subsidies affect low-carbon supply-chain coordination and pricing decisions [14]. These studies support the present finding that sales forecasting should not treat consumer price as an isolated market variable; it is the downstream result of supply-chain contracts, production conditions, distribution costs, and strategic decisions.

The positive effects of installment-payment availability and price reduction in the scenario analysis indicate that firms can increase adoption by reducing the immediate financial burden rather than relying exclusively on promotional communication. This conclusion is also compatible with research on revenue-sharing and sales-effort coordination, which suggests that channel members can improve outcomes when contractual incentives support both quality and market expansion [15]. From a system dynamics perspective, improved affordability enlarges the effective potential market, accelerates the flow of consumers into the adopter stock, and increases the number of users who can subsequently generate favorable word of mouth. Thus, price interventions may have both direct economic effects and indirect social effects.

Perceived risk was the strongest negative predictor of purchase intention and also significantly delayed early adoption. This finding indicates that consumers hesitate when they are concerned about financial loss, poor performance, rapid obsolescence, security problems, incompatibility, weak after-sales services, or insufficient warranty support. The scenario involving negative early-user reviews produced a particularly large decline in cumulative sales, demonstrating that unfavorable experiences can transform the word-of-mouth mechanism from a reinforcing growth loop into a reinforcing decline loop. This result is consistent with research showing that perceived risk mediates the relationship between salesperson behavior and consumer loyalty [26]. It also supports the broader conclusion that marketing factors influence customer retention through perceived value and confidence in the overall offer [8]. In new-product markets, reducing risk may therefore be as important as increasing perceived benefits.

Technological innovativeness significantly predicted purchase intention and early adoption, although its effect was smaller than the effects of usefulness, affordability, and word of mouth. This result suggests that innovative consumers are more willing to experiment with newly introduced electronic products, but their behavior is still constrained by price and risk. The subgroup findings supported this interpretation: the youngest respondents demonstrated high technological innovativeness but lower perceived affordability. Therefore, an interest in technology does not automatically translate into purchasing power. This distinction is important for sales prediction because models based only on consumer enthusiasm may overestimate actual demand. New-product forecasting models should therefore distinguish between attitudinal readiness and economically feasible adoption.

The structural model explained a substantial proportion of the variance in purchase intention and early adoption, while the dynamic model reproduced most of the variation in sales volume with relatively low prediction error. These findings are consistent with the growing use of artificial intelligence and hybrid forecasting methods for nonlinear and short-cycle demand. Studies have shown that smart predictive methods can support pharmaceutical sales forecasting [4], while artificial-intelligence approaches have been applied to sales prediction in Iran's pharmaceutical industry [3]. A hierarchical RF-XGBoost model has likewise demonstrated the value of hybrid learning for short-cycle product sales [5]. The present study contributes to this literature by emphasizing causal structure, feedback, time delays, and scenario simulation rather than prediction accuracy alone. This provides greater interpretability and allows managers to evaluate how sales may change under different market conditions.

The simulated sales curve followed the expected pattern of innovation diffusion. Sales were initially limited because awareness was low and few consumers had direct experience with the product. Growth accelerated when increasing adoption improved visibility, legitimacy, trust, and online communication. Monthly sales eventually reached a peak and then declined as the remaining potential market became smaller and the pool of late adopters became more price-sensitive and risk-averse. This pattern is consistent with research on the interaction of consumer heterogeneity, user reviews, and sales over the product life cycle [22]. It is also compatible with forecasting research on newly released mobile phones, where sales patterns are shaped by short product life cycles and rapidly changing market information [6]. The system dynamics framework captured this process through reinforcing growth loops and balancing saturation loops.

The green-product and sustainability literature also provides a useful interpretation of the product-attractiveness mechanism. Consumers' green purchase intentions are influenced by attitudes, trust, knowledge, and perceived behavioral control [17]. Responsibility for green-product development may also be allocated differently between manufacturers and retailers, affecting supply-chain incentives and market performance [16]. A green-marketing model developed to increase product sales further indicates that sustainability can become a strategic source of product differentiation [18]. Although environmental attributes were not the dominant variables in the present analysis, energy efficiency, durability, repairability, and responsible production can strengthen perceived quality and relative advantage and may therefore improve future electronic-product sales.

The findings also emphasize the importance of information support and managerial coordination. The successful application of a dynamic forecasting model requires reliable data, clear procedures, and integration across sales, marketing, procurement, distribution, and after-sales service. Research on information and procedural support for sales management has similarly emphasized the value of structured information systems for brand and sales decision-making [27]. Furthermore, the implementation of forecasting systems depends on organizational leadership, management practices, and employee motivation. Although examined in a different institutional context, research showing that leadership and management practices foster productive environments supports the broader importance of organizational readiness for using analytical systems effectively [28]. A technically accurate model will have limited practical impact unless decision-makers understand its assumptions and translate its scenarios into coordinated action.

This study had several limitations. First, the data were collected through a cross-sectional field survey of consumers aged 15 to 29 years in Tehran, which limits the generalizability of the findings to older consumers, rural populations, and other Iranian cities with different economic and retail conditions. Second, the behavioral variables were based on self-reported perceptions and expected adoption timing rather than verified purchasing records, creating the possibility of common-method bias and discrepancies between stated intentions and actual behavior. Third, the simulated sales volumes were derived from survey-based parameter estimates and a normalized potential market rather than from the observed launch history of a single electronic product. Fourth, the model simplified some market processes, including competitor reactions, exchange-rate shocks, regulatory restrictions, product substitution, retailer inventory limitations, and brand-specific differences. Finally, although sensitivity and validation procedures supported model stability, the accuracy of system dynamics models remains dependent on the assumptions, parameter values, and feedback structures selected by the researchers.

Future studies should validate the proposed model using longitudinal sales data from actual electronic-product launches and compare predicted values with weekly or monthly retail transactions. Researchers should extend sampling to multiple Iranian cities and include broader age, income, and occupational groups. Future models could incorporate exchange rates, inflation, import restrictions, competitor prices, product shortages, and online search trends as time-varying variables. Comparative analyses could also determine whether the model performs differently for smartphones, laptops, wearables, gaming devices, household electronics, and environmentally sustainable products. Integrating system dynamics with machine-learning techniques may improve both predictive accuracy and causal interpretability. Future research should additionally examine whether positive and negative user reviews have asymmetric effects, whether influencer credibility changes adoption speed, and how brand reputation moderates the impact of product defects or service failures.

Managers introducing new electronic products should prioritize clear demonstrations of usefulness, technical quality, relative advantage, warranty reliability, and after-sales support. Pricing strategies should reflect the purchasing capacity of young consumers, with installment plans, introductory discounts, trade-in programs, and flexible payment arrangements used to reduce adoption barriers. Marketing resources should not be concentrated solely on advertising; firms should actively manage early-user experience, customer reviews, product communities, and post-purchase support because favorable word of mouth can generate sustained sales growth. Negative reviews and service failures should be addressed rapidly before they become reinforcing sources of market decline. Firms should also use scenario-based forecasting to coordinate inventory, promotional timing, distribution capacity, and service resources under alternative economic conditions. The dynamic model can be updated continuously with actual sales and consumer-response data so that managers can identify deviations from the expected trajectory and adjust pricing, communication, and supply decisions before losses accumulate.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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References

[1] M. Tahiri, "Ranking and identifying the factors affecting the marketing and sales of new products for the production of electrical energy (solar panel) - a case study of Fars Province Electricity Distribution Company," Master's Thesis, 2019. [Online]. Available: https://ganj.irandoc.ac.ir/#/articles/c41b181a19c1bc8e64fefbac74af6e39

[2] E. Fallahi and S. Khalilian, "Comparison of the importance of petroleum products and electricity with other production factors in Iran's agricultural sector," *Journal of Agricultural Economics Research,* vol. 1, no. 2, 2009 2009. [Online]. Available: https://www.sid.ir/paper/158612/.
[3] A. Mahban, K. Hamdi, and P. Ghafari Ashtiyani, "Forecasting product sales in Iran's pharmaceutical industry using artificial intelligence," *Journal of Marketing Management,* vol. 66, pp. 77-94, 2025.
[4] S. R. Dutta, S. Das, and P. Chatterjee, "Smart sales prediction of pharmaceutical products," in *2022 8th International Conference on Smart Structures and Systems (ICSSS)*, 2022: IEEE, pp. 1-6, doi: 10.1109/ICSSS54381.2022.9782271.
[5] J. Li *et al.*, "A Hierarchical RF-XGBoost Model for Short-Cycle Agricultural Product Sales Forecasting," *Foods,* vol. 13, p. 2936, 2024, doi: 10.3390/foods13182936.
[6] S. Hwang, G. Yoon, E. Baek, and B.-K. Jeon, "A Sales Forecasting Model for New-Released and Short-Term Product: A Case Study of Mobile Phones," *Electronics,* vol. 12, no. 15, p. 3256, 2023, doi: 10.3390/electronics12153256.
[7] K. Aminah, W. Hermawan, and D. Budiana, "Product Purchasing Decisions as a Result of Product Innovation and Sales Promotion," *Almana: Jurnal Manajemen dan Bisnis,* vol. 6, no. 1, pp. 144-158, 2022, doi: 10.36555/almana.v6i1.1821.
[8] m. Darvishi, "Investigating the effect of marketing mix factors (product, price, after-sales service, location) on customer retention by considering the mediating role of perceived customer value (Case study: customers of Digistyle clothing online store," (in en), *Journal of Intelligent Marketing Management,* vol. 2, no. 6, pp. 93-106, 2022. [Online]. Available: https://www.jnabm.ir/article_251717.htmlhttps://www.jnabm.ir/article_251717_69e11373b95a906dbdcdf0d784f1b6b8.pdf.
[9] C. Lan and J. Zhu, "New Product Presale Strategies Considering Consumers' Loss Aversion in the E-Commerce Supply Chain," *Discrete Dynamics in Nature and Society,* vol. 2021, pp. 1-13, 2021, doi: 10.1155/2021/8194879.
[10] W. Hu, J. Ding, P. Yin, and L. Liang, "Dynamic pricing and sales effort in dual-channel retailing for seasonal products," *Journal of Industrial & Management Optimization,* vol. 19, no. 2, 2023, doi: 10.3934/jimo.2022005.
[11] C. Zhang and J. Wu, "Wholesale price confidentiality under demand uncertainty in competing supply chains," *International Journal of Production Economics,* p. 109804, 2025, doi: 10.1016/j.ijpe.2025.109804.
[12] S. Schiffels and G. Voigt, "Capacity reservation and wholesale price contracts under forecast sharing: A behavioral assessment," *Production and Operations Management,* vol. 30, no. 10, pp. 3579-3598, 2021, doi: 10.1111/poms.13451.
[13] T. A. Basith and A. A. Sajith, "Impact of wholesale price contracts in two-echelon supply chains under production disruptions," Lisbon, Portugal, 2023.
[14] F. Ren and B. Hu, "Decisions and coordination in low-carbon supply chains with a wholesale price constraint under government subsidies," *International Journal of Production Economics,* vol. 277, p. 109407, 2024, doi: 10.1016/j.ijpe.2024.109407.
[15] M. Nakhaeinejad, A. Dehghan, and N. S. Vaziri, "Developing a supply chain coordination model through a revised revenue sharing contract: Incorporating sales efforts and green quality considerations," *International Journal of Production Management and Engineering,* vol. 13, no. 1, pp. 102-121, 2025, doi: 10.4995/ijpme.2025.20402.
[16] B. Li, H. Wang, and W. Zheng, "Who will take on green product development in supply chains? Manufacturer or retailer," *Journal of Cleaner Production,* vol. 314, p. 128000, 2021/09/10/ 2021. [Online]. Available: https://doi.org/10.1016/j.jclepro.2021.128000.
[17] R. Wijekoon and M. F. Sabri, "Determinants That Influence Green Product Purchase Intention and Behavior: A Literature Review and Guiding Framework," *Sustainability*, vol. 13, no. 11, doi: 10.3390/su13116219.
[18] A. Mehban, K. Hamdi, and P. Ghaffari Ashtiani, "Presenting a Green Marketing Model to Increase Pharmaceutical Product Sales," *Green Development Management Studies,* vol. 14, no. 7, pp. 121-177, 2024.
[19] R. Hadiyati, "From Content to Commerce: Investigating the Role of Content Marketing in Driving Sales and Brand Engagement," *Productivity,* vol. 1, no. 3, pp. 355-368, 2024, doi: 10.62207/sntdc635.
[20] T. Pusriadi and Sudarmiatin, "Inbound marketing strategy: Marketing concept to increase sales of small and medium enterprises (SMEs) products in Indonesia," *International Journal of Academic Research in Business and Social Sciences,* vol. 11, no. 5, pp. 730-736, 2021, doi: 10.6007/IJARBSS/v11-i5/9888.
[21] F. Mataji Nimvari , S. Kari , and A. Aghajanpour "Conceptualization of Advertising, brand credibility and sales strategy," (in Fa), *Journal of New research approaches in management and accounting,* vol. 5, no. 56, pp. 189-197, 2021. [Online]. Available: https://www.magiran.com/paper/2275168.
[22] Y. Lin and L. Jen, "The Impact of Consumer Heterogeneity in the Product Life Cycle on the Diffusion Patterns of User Reviews and Sales," *Journal of Retailing and Consumer Services,* 2024.
[23] N. Mohaghegh and M. Amouhoma, "Investigating and identifying the sales triggers for luxury products of Iran Khodro (Tara product) in emerging markets with a competitive advantage strategy to influence the determining factors of customer loyalty and relationships on social media," *Journal of Management Science Research,* vol. 3, no. 9, pp. 137-153, 2021. [Online]. Available: https://unitesi.unive.it/handle/20.500.14247/4987.
[24] N. Mohaghegh, M. Amooamoo, and S. Hashemi Salehi, "Investigating and identifying the sales drivers of Iran Khodro luxury products (Tara product) in emerging markets with a competitive advantage strategy to influence the determinants of customer loyalty and customer relationships in social media Legal principles of franchise and trademark license contracts

in the legal system of Iran and Malaysia," *Journal of Management Sciences Research,* vol. 3, no. 9, pp. 137-153, 2021. [Online]. Available: https://civilica.com/doc/1500938/.

[25] N. Mohegh and M. Amoo-amooha, "An investigation and identification of the sales drivers of Iran Khodro's luxury products (Tara model) in emerging markets through a competitive advantage strategy: Assessing their impact on key factors influencing customer loyalty and customer relationships in social media," *Journal of Management Science Research,* vol. 3, no. 9, pp. 137-153, 2021. [Online]. Available: https://civilica.com/doc/1500938/.

[26] A. Kazemi and M. Emami, "Investigating the effect of professional dimensions of sale person behavior on consumer loyalty through the mediating role of Enjoyable Interaction and perceived risk (Case of Rahsazan Tabiat Safahan Cooperative Company," *Consumer Behavior Studies Journal,* vol. 9, no. 2, pp. 137-157, 2022, doi: 10.34785/j018.2022.454.

[27] V. Lazebnyk, "Information and Procedural Support for Sales Management in the Segment of Profitable Organic Product Brands," *Electronic Scientific Journal Intellectualization of Logistics and Supply Chain Management #1 2020,* no. 32, pp. 32-41, 2025, doi: 10.46783/smart-scm/2025-32-2.

[28] S. Sariakin, M. Yeni, M. B. Usman, A. S. Mare, M. Munzir, and M. Saleh, "Fostering a productive educational environment: The roles of leadership, management practices, and teacher motivation," *Frontiers in Education,* vol. 10, 2025.