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Prioritizing disruptive information technologies in Fashion E-Commerce using OSINT

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Abstract: The article addresses the marketing problem of ranking the impact magnitude of disruptive information technologies (disruptive IT) on customers and sales, while avoiding unjustified expenses in the field of Fashion E-commerce. The task is to develop a methodology for ranking the influence of disruptive IT in order to determine their implementation priority in the development of Fashion E-commerce. A hypothesis is proposed: based on relevant and reliable information from legal open sources regarding the consequences of applying disruptive IT in the Fashion E-commerce sector, it is possible to identify, classify, and assess the degree of their impact on digital transformation in Fashion E-commerce. This, in turn, can be used to objectively determine the priority of implementing disruptive IT. The object of the study is disruptive IT; the subject is the consequences of implementing disruptive IT. The criteria for assessing the consequences include economic effect, impact on UX (user experience), risks, and social response. The article proposes the use of content analysis methods applied to relevant and reliable information obtained from OSINT search tools using legal open digital sources. Content analysis involves the identification of key topics, terms, emotional markers, and statistical patterns in textual, visual, and multimedia messages related to the implementation of disruptive IT in Fashion E-commerce. OSINT search tools ensure the representativeness of selected keywords, the completeness of relevant source coverage, and the balance between synonyms/variations of terms to obtain reliable information. An approximate mathematical model of data sample representativeness, based on queries with N keywords/phrases, is substantiated. It is proven that at least 5–10 well-chosen keywords/phrases are required for each topic/category. As a result of comparing statistical indicators with managerial criteria such as ISO 31000 and MIL-STD, the possibility of applying statistical indicators of the approximate mathematical model of data sample representativeness to decision-making regarding the degree of disruptive IT influence on Fashion E-commerce is justified. The article describes a methodology for ranking the impact magnitude of disruptive IT on the development of Fashion E-commerce and provides an example of applying such ranking to determine their implementation priority in the industry's development. A justified ranking of disruptive IT has been obtained, namely: AI/ML, VR/AR, Big Data and analytics, IoT/RFID, among others. The results can be used for strategic planning and the formation of innovative business models in the field of online fashion retail.

Keywords: E-commerce, Fashion E-commerce, Disruptive information technologies, Open Source Intelligence, Content analysis

1. Introduction

Fashion E-commerce today is exceptionally dynamic. It is not merely the online sale of fashion apparel—it encompasses a comprehensive set of consumer expectations. Customers demand a wide assortment, regular product updates, fast delivery, and seamless returns. Moreover, they increasingly expect all these services to be personalized to their individual preferences. Consequently, brands are compelled to adapt their processes and search for innovative organizational models [1, 2].

Disruptive information technologies create conditions for business innovation in Fashion E-commerce. The ranking of breakthrough IT technologies is considered (artificial intelligence/machine learning (AI/ML), virtual reality/augmented reality (VR/AR), big data and analytics, Internet of Things/radio frequency identification (IoT/RFID), etc.). For instance, AI/ML-driven recommendation systems suggest products most likely to appeal to specific customers. VR/AR technologies deliver immersive online shopping experiences, simulating product "try-ons" in front of a screen. Blockchain and smart contracts enable the issuance of digital ownership certificates for virtual fashion products. Big Data and social analytics allow brands to optimize marketing campaigns and even uncover new revenue channels. Brands are actively adopting disruptive technologies for generative design, rapid 3D rendering, and accelerated production. However, the adoption of disruptive technologies also entails risks: significant implementation costs, the need for skilled professionals, and sometimes unpredictable consequences for business processes. This is driven by several factors, including the multidimensionality of effects (economic, social, behavioral, logistical), the high dynamism of the digital environment, the bidirectional nature of outcomes (both positive and negative), regional differences in adoption, and the shortage of reliable, structured, and verified data. Subjectivity in expert assessments and the absence of unified measurement criteria create additional barriers. As a result, neither scholars nor practitioners currently possess universal tools for objectively determining the priority of disruptive IT adoption in Fashion E-commerce [3, 4, 5].

Problem Statement. For marketing, the ranking of disruptive IT in Fashion E-commerce provides a means to systematize chaotic innovations, identify the technologies with the greatest impact on customers and sales, and avoid unwarranted costs. In fact, ranking transforms "technology trends" into a brand's strategic advantage. Despite the increasing role of disruptive IT in the digital transformation of Fashion E-commerce, a standardized methodology for quantitatively and qualitatively ranking their impact is still lacking. Therefore, the task arises of developing a methodology for ranking the impact of disruptive IT to determine their priority for implementation in Fashion E-commerce development.

2. Object and subject of research

The object of the research is disruptive information technologies (disruptive IT) that exert influence on the digital transformation of the Fashion E-commerce sector, with their properties and parameters defined within this study.

The subject of the research is the consequences of implementing disruptive IT, assessed through specific criteria of impact, namely: economic effect, influence on user experience (UX), associated risks, and societal response.

3. Target of research

To enhance the effectiveness of business process management through the development of a universal toolkit for objectively determining the priority of disruptive IT implementation in Fashion E-commerce.

4. Literature analysis

Numerous academic publications are devoted to the integration of disruptive IT into Fashion E-commerce processes. Diverse aspects are discussed, such as theoretical and practical perspectives [6, 7]. Artificial intelligence applications are explored in [8], augmented/virtual reality in retail is discussed in [9], statistical data on global Fashion E-commerce is presented in [10], robotics in [11], Big Data and analytics in [12], and blockchain in [13]. However, the issue of ranking disruptive IT in Fashion E-commerce has not yet been addressed. This defines the following research objective.

5. Research methods

The article employs a comprehensive set of methods that integrate OSINT data search tools, content analysis, mathematical modeling, and comparison with risk management standards. A detailed description is provided below:

1. OSINT Methods (Open Source Intelligence). These involve the use of legal open digital sources (official websites, blogs, social networks, scientific publications, patent databases, analytical reports) with the help of OSINT tools such as Google Dorks, Wayback Machine, Social Searcher, Shodan, Maltego, SpiderFoot, Hunter.io, Google Trends, among others. This ensures the collection of a maximally representative dataset on disruptive IT in Fashion E-commerce. The representativeness of the sample is guaranteed by using at least 5–10 keywords/phrases per topic.

2. Content Analysis. This method is applied to process the collected information from open sources and includes the following stages: (1) defining categories (topic, tonality, source, audience); (2) collecting content from OSINT sources; (3) coding data (identifying patterns, keywords); (4) cleaning noise (spam, duplicates); (5) lemmatization and NLP analysis (identifying technologies, brands, emotional markers); (6) constructing thematic matrices and trend analysis; (7) sentiment analysis (VADER, TextBlob); (8) verification through expert evaluation and KPI. The result is the identification of key disruptive technologies and the assessment of both positive and negative consequences of their implementation.

3. Mathematical Modeling of Sample Representativeness. An approximate statistical model was developed based on probability theory, applying the formula for the confidence interval of proportions. This allows for a quantitative assessment of the accuracy of OSINT search results and the representativeness of the data.

4. Methodology for Ranking Disruptive IT. The approach includes the following steps: (1) identification and selection of keywords; (2) data collection from OSINT sources; (3) content analysis (classification by categories such as marketing, UX, logistics, security, etc.); (4) construction of “technology – domain – consequence” matrices; (5) visualization of results (charts, diagrams, Maltego); (6) comparison with KPI (conversion rate, engagement, forecasting accuracy, CSAT, ROI, etc.).

5. Verification Methods and Management Standards. Comparison of statistical findings with international standards such as ISO 31000 (risk management) and MIL-STD (engineering decision-making methodologies) enables the evaluation of risks, data reliability, and their applicability for strategic planning.

As a result, the integration of OSINT + content analysis + mathematical modeling + ISO/MIL standards produced a methodology for ranking the impact of disruptive IT (AI/ML, VR/AR, Big Data, IoT/RFID, Blockchain, Chatbots, MarTech, Deep Learning).

6. Research results

6.1 Theoretical Justification of the Methodology for Ranking the Impact of Disruptive IT on the Development of Fashion E-commerce. The ranking methodology is based on the systematic organization of information derived from diverse knowledge sources, taking into account their relevance and reliability. To obtain valid and relevant information on the consequences of disruptive IT adoption in Fashion E-commerce, legally accessible open sources are employed, including official websites, professional blogs, academic publications, social media platforms, specialized IT portals, patent databases, and analytical reports. Based on this information, an analysis is conducted to assess the degree of positive or negative impact of a given disruptive IT.

The methodology relies on the following scientific hypothesis: by using relevant and reliable information from legal open sources regarding the effects of disruptive IT in Fashion E-commerce, it is possible to identify, classify, and assess the degree of their impact on digital transformation in the industry. This approach may serve as an objective basis for determining the priority of disruptive IT implementation.

Within this framework, the object of study is disruptive IT influencing digital transformation in Fashion E-commerce; the subject of study is the consequences of disruptive IT adoption. The criteria for evaluating the impact of disruptive IT include economic effect, user experience (UX), risks, and social response. To test this hypothesis, content analysis of relevant and reliable information obtained through OSINT search tools from open digital sources is applied. Popular OSINT tools for data extraction from open digital sources are presented in Table 1 [14, 15].

Table 1. Popular OSINT tools (author's development)

Tool / platform Purpose	Purpose
Social Searcher	Monitoring of mentions in social networks.
Talk walker, Brand 24	Social media analysis, collection of publications from social networks.
Shodan	Search for open IoT devices and services on the network.
Censys	Shodan alternative, deeper analysis of SSL/certificates.
Have I Been Pwned	Checking for leaks of passwords and email addresses.
Maltego	Visual reconnaissance of connections (domains, IPs, organizations).
Spider Foot	Automatic collection of information about the target.
The Harvester	Collection of email addresses, domains, IPs.
Built With	Technologies on a competitor's website.
DNS dumpster	Determining DNS records, subdomains

Content analysis involves the identification of key themes, terms, emotional markers, and statistical patterns in textual, visual, and multimedia messages related to the implementation of disruptive IT in Fashion E-commerce. The operational algorithm of OSINT tools and content analysis is presented in Table 2 [16, 17].

Table 2. Algorithm of Content Analysis (author's development)

Stage	Actions	Tools / Methods	Goal / Outcome
1.	Defining analysis categories	Topic, tone, source type, target audience	Establishing what to look for and how to differentiate it
2.	Collecting content from open sources	OSINT tools, e.g., Google Dorks, Social Search, Scraper, etc.	Aggregating relevant content from social media, forums, and mass media
3.	Coding and interpretation	Text patterns, regular expressions, Python scripts	Extracting and classifying patterns, counting keywords
4.	Initial data cleansing	Manual or automated filtering	Removing noise: duplicates, spam, irrelevant content

Continuation of Table 2

Stage	Actions	Tools / Methods	Goal / Outcome
5.	Lemmatization and keyword extraction	NLP algorithms (e.g., spaCy, NLTK)	Identifying important words: technologies, brands, emotional ratings
6.	Building thematic frequency matrices	Statistical analysis, matrix representation, text vectorization	Defining topics and frequency of mentions for further trend analysis
7.	Identifying trends by frequency and tone	Comparative analysis of frequencies and tone changes	Detecting growth/decline in interest in topics or brands
8.	Analyzing the tone of messages	VADER, TextBlob (*)	Determining the emotional rating of texts (positive / negative / neutral)
9.	Verifying results	Expert evaluation, comparison with business KPIs	Confirming the reliability of the results by comparing them with real data

(*) - VADER—a lexicon-based sentiment analysis tool; TextBlob—a library for automated sentiment detection.

The integration of content analysis with OSINT search tools from legally accessible open digital sources enables an in-depth investigation of the consequences of disruptive IT adoption in Fashion E-commerce. This approach ensures objective, scalable, and representative evaluation of digital trends, allowing researchers to identify both successful cases of disruptive technology implementation in Fashion E-commerce and the associated risks or social reactions.

6.2 Conditions for obtaining relevant and reliable information using OSINT tools. OSINT search tools based on legally accessible open digital sources must rely on a representative sample in order to provide accurate and reliable information. From the perspective of probability theory and statistics, a representative sample is one that adequately reflects the key characteristics of the general population of information under investigation. This implies that the sample should be random, sufficiently large, reflect the main features of the target information, and minimize estimation error.

Information retrieval on the Internet is conducted through search queries (keywords). In the context of OSINT-based searches, keyword selection directly affects the representativeness of the data sample, the completeness of coverage of relevant sources, and the balance between synonyms and term variations. Unlike in classical statistics, the margin of error and confidence level are not directly calculated as in survey sampling [18]. However, it is possible to approximate a statistical approach when the OSINT search process relies on large volumes of textual data, such as news articles, posts, and mentions. Thus, unlike traditional statistics, there is no “fixed number” here, but rather practical methodological approaches [19].

6.2.1 The essence of the practical approach. The practical approach assumes the existence of an approximate mathematical model of sample representativeness. This model may be applied if the population is understood as the entire body of online information on a specific topic; the sample—as data obtained from queries using N keywords/phrases; the objects of study—as posts, news items, and mentions; and the subject of study—as the consequences of disruptive IT adoption in Fashion E-commerce. Hence, an approximate confidence interval model for error in proportions can be applied [20].

$$MOE = z * \sqrt{\frac{p(1-p)}{n}} \quad (1)$$

where:
- MOE — Margin of Error,
- z — confidence coefficient (1.96 for a 95% confidence level),
- p — proportion of positive mentions / relevance,
- n — number of retrieved documents.

For example: if, out of 1,000 documents retrieved by predefined keywords, 600 are relevant (p= 0.6), then:

$$MOE = 1{,}96 * \sqrt{\frac{0{,}6(1-0{,}4)}{1000}} \approx 0{,}03 \quad (2)$$

This means that, with 95% probability, the true proportion of relevant results lies within ±3%.

From the practical perspective of applying OSINT search tools, it is currently considered necessary to use *N* well-selected keywords or phrases per topic/category—at least 5–10. The figure of 5–10 is a commonly accepted practice, tested in real OSINT projects [21]. This minimum is required in order to: cover semantic diversity (synonyms, abbreviations, professional terms); reduce informational bias and noise; standardize queries across different sources (Google, Shodan, Twitter, Pastebin, etc.).

The definitions of the main OSINT parameters are provided in Table 3 [22].

Table 3. Definitions of the main OSINT parameters [22].

Parameter	Value
Number of keywords	5–10 per topic (minimum)
Confidence level	~90–95% (if the sample is properly collected)
Content-related margin of error	~5–10% (assuming good keyword selection)
Statistical margin of error	~2–5% (if number of results > 500)

6.2.2 When oriented toward a risk management approach, it is possible to align statistical indicators with managerial criteria based on ISO 31000 (risk management), MIL-STD (engineering decision-making methodologies) [23, 24] (Table 4).

Table 4. Alignment of statistical indicators with managerial criteria according to ISO 31000, MIL-STD [23, 24]

Statistical Indicator	Range / Conditions	Managerial Criteria	Approximate Risk Level
Confidence level	~90–95% (with proper sampling)	Reliability ≥ 95% (for minimal risk)	Low risk (≤5%)
Statistical error	~2–5% (if n > 500)	Part of reliability criterion (80–95%)	Controlled risk
Sample representativeness	sufficient ($n \geq 500$, stratification applied)	Criticality = high (information affects decision-making)	Minimal risk
Content-related error	~5–10% (with well-formulated queries)	Relevance ≥ 70–90%	Medium → low risk, depending on the task
Sample representativeness	sufficient (n ≥ 500, stratification applied)	Criticality = high (information affects decision-making)	Minimal risk

From Table 4, it can be observed that:

- If the confidence level ≥ 95% and the statistical error ≤ 5%, this corresponds to reliability according to managerial standards (ISO/MIL) at a level of ≥ 95%.
- If the content-related error ≤ 10%, this approximates a relevance of ≥ 90%, meaning the information practically fully meets the research objectives.
- Taken together, these three indicators provide an informational basis for decision-making with minimal risk.

6.2.3 A dataset can be considered representative for a given topic if the factors listed in Table 5 are taken into account [22].

Table 5. Factors Influencing the Number of Keywords (author's development)

Factor	Recommendation
Topic complexity (e.g., IT, social media)	The more complex the topic, the more keyword variations are needed (10–50)
Search language	Add queries in multiple languages (e.g., English, Ukrainian, German, etc.)
Search platforms	Adapt queries to platform-specific features (e.g., Google ≠ GitHub ≠ Telegram)
Synonyms and abbreviations	Use variations such as: *VPN breach, VPN cracked, VPN auth leak*
Target source	For monitoring the darknet or paste sites, use more "low-level" or informal terms

A recommended approach exists for creating representativeness. Its essence is as follows:

1. Compile a core set of more than 5–10 keywords.
2. Add 2–3 synonyms or alternative spellings for each keyword.
3. Use logical operators (AND, OR, site:, filetype:) to structure the queries.
4. Test search results: if results begin to repeat or show little variation, the semantic coverage is considered sufficient.
5. Apply tools that assist in keyword selection (see popular OSINT tools in Table 1).

From this, 10+ variants can be generated, which already create a representative basis for data collection on a given topic. To further improve the representativeness of an OSINT search, it is advisable to have 10–20 unique, contextually relevant keyword queries adapted to different sources and languages.

6.3 Description of the methodology for ranking the impact of disruptive information technologies on the development of Fashion E-commerce. The methodology involves the following steps:

6.3.1 To obtain relevant and reliable information using OSINT tools, keywords are identified to form OSINT search queries with the help of various means, examples of which are provided in Table 6 [25].

Table 6. Tools for keyword generation in OSINT (author's development)

Tool / Platform	Purpose
Automatic keyword generation tools	
Google Keyword Planner	Generates related keyword phrases based on a given topic
AnswerThePublic	Produces dozens of keyword variants and questions
SEMrush / Ahrefs / Ubersuggest	SEO tools for creating search queries in search engines and social media

Continuation of Table 6

Tools specifically for OSINT or SOCMINT	
Maltego	Generates keywords based on related persons, domains, IP addresses, locations, etc.
IntelTechniques Keyword Tools	Ready-made keyword lists for social media, darknet, Google, Bing, Twitter, Facebook, etc.
SpiderFoot	Collects information from multiple sources and can generate additional target keywords (names, aliases, domains, IPs, etc.)
Lampyre	Generates many related keywords based on a single object
Manual generation tools	
Google Search Operators	Allows manual construction of flexible keyword queries using operator combinations (site:, inurl:, filetype:, intitle:)
NLP approaches (Natural Language Processing)	Tools such as spaCy, NLTK, or ChatGPT can analyze text and automatically extract keywords
LLM usage (ChatGPT, Claude, etc.)	Provides keyword lists automatically based on a given prompt
OSINT Cheat Sheets (ready-made templates)	
OSINT Framework	Contains links to tools and predefined queries
Michael Bazzell's OSINT Tools & Resources	Ready-made keywords and queries for searching people, objects, accounts, emails, etc.
Hunchly Google Dork List	List of useful search queries (dorks) for generating relevant results

6.3.2 Using OSINT tools, data collection is performed to aggregate textual and multimedia content. Relevant OSINT sources are defined as legally accessible open sources of information.

6.3.3 Content analysis is applied to verify and classify the relevant and reliable information obtained through OSINT searches:

- The collected data are coded according to thematic categories: type of technology, area of application, level of impact (high, medium, low), and nature of consequences (positive, negative).
- Information is structured by marking technology mentions.
- Categorization is performed by impact domains (marketing, UX, logistics, security) and classified by fields: logistics, UX, marketing, cybersecurity.

Based on the structured data, a systematized list of the most relevant and promising disruptive technologies is formed, reflecting their real impact on digital transformation in Fashion E-commerce, with qualitative and quantitative descriptions of the nature and scale of their consequences. Positive and negative effects are assessed, and conclusions are drawn regarding the priority of disruptive IT for implementation in Fashion E-commerce. The result of content analysis is the creation of tables capturing the qualitative and quantitative consequences of impact, including fields such as technology name, domain, consequence, and source.

6.3.4 The results of the analysis are visualized through graphs of the structured data (a matrix of "technology – domain – consequence").

6.4 Example of applying disruptive IT impact ranking to determine their priority for implementation in the development of Fashion E-commerce. To address this task, we begin by identifying keywords and corresponding search queries on the topic: *"set of disruptive IT in Fashion E-commerce, their consequences, and applications."*

6.4.1 Implementation of Step 3.1 of the methodology. To improve the representativeness of the OSINT search, 40 unique, contextually relevant keyword queries were selected, adapted for different sources and languages using Google Keyword Planner. An example is provided in Table 7.

Table 7. Keywords and corresponding search queries for the topic “Set of disruptive IT in Fashion E-commerce” (author's development)

Category	Keyword/Phrase (EN)	Keyword/Phrase (UA)	Example Google Search Query
1. Technologies	AI in fashion e-commerce	Штучний інтелект у fashion e-commerce	"AI in fashion e-commerce applications"
	Augmented reality fitting	AR-примірка	"Augmented reality fitting room online shopping"
	Virtual try-on	Віртуальна примірка	"Virtual try-on technology for clothing"
	3D product visualization	3D-візуалізація товарів	"3D visualization fashion products site"
	Chatbot for fashion store	Чат-бот для онлайн-магазину одягу	"Fashion e-commerce chatbot integration"
	AI-generated models	Моделі, створені штучним інтелектом	"AI-generated fashion models e-commerce"
2. Analytics	Predictive analytics fashion	Прогнозна аналітика в модній торгівлі	"Predictive analytics in fashion retail"
	Customer behavior tracking	Відстеження поведінки покупців	"Customer behavior tracking tools for fashion e-commerce"
	Big data in retail	Великі дані у рітейлі	"Use of big data in fashion retail"
3. Marketing	Personalization engine	Система персоналізації	"Product personalization engines for online clothing stores"
	AI-based recommendations	Рекомендаційні системи на базі ШІ	"AI recommendation system fashion website"
	Omnichannel strategy	Омніканальна стратегія	"Omnichannel marketing strategy fashion e-commerce"
4.UX / UI	Adaptive design	Адаптивний UX/UI дизайн	"Adaptive UX/UI design for fashion e-commerce"
	Voice commerce	Голосова комерція	"Voice search in fashion e-commerce"
	Visual search	Візуальний пошук	"Visual search technology for clothes online"
5. Security	Payment gateway security	Безпека платіжних систем	"Secure payment gateways fashion e-commerce"
	Cyber risk in fashion e-commerce	Кіберризики у модній електронній торгівлі	"Cybersecurity threats in online fashion retail"

Continuation of Table 7

6. Industry Trends	Fashion tech startups	Стартапи в галузі fashion-tech	"Top fashion tech startups 2025"
	Future of fashion e-commerce	Майбутнє fashion e-commerce	"Future trends in fashion e-commerce technology"
	Sustainable fashion tech	Технології сталого розвитку у моді	"Sustainable technology innovations in fashion retail"

6.4.2 Step 3.2 of the methodology is implemented. Based on the keywords and corresponding search queries, a set of disruptive IT in Fashion E-commerce is identified with a 95% probability of relevant results within ±3%, along with the corresponding consequences of their application (Table 8).

Table 8. Set of disruptive IT in Fashion E-commerce and their application consequences (author's development)

№	Information Technology	Positive Consequences	Negative Consequences
1	AI / ML	Personalized recommendations, supply chain optimization, order automation, increased conversion	Risks of manipulation, loss of privacy
2	AR / VR	Improved customer experience, reduced returns, increased customer engagement	Technical implementation challenges
3	Big Data / Analytics	Trend analysis, demand forecasting, marketing campaign optimization, increased profitability	Data privacy issues
4	IoT / RFID	Warehouse automation, interactive stores, improved logistics	Vulnerability to cyber threats
5	B&SC	Supply chain transparency, product authenticity verification, anti-counterfeiting	High implementation cost
6	CBVA	Improved customer service quality, 24/7 support, reduced staff workload	Risk of incorrect or misleading responses
7	MarTech	Personalized promotion, improved advertising effectiveness	Overly intrusive advertising
8	DL / CNN / GAN	Photorealistic virtual models, enhanced visual content	Ethical issues related to deepfake technology

Note: AI/ML – Artificial Intelligence and Machine Learning; AR/VR – Augmented Reality and Virtual Reality; Big Data / Analytics – Big Data and consumer analytics; IoT/RFID – Internet of Things and Radio-Frequency Identification; B&SC – Blockchain and Smart Contracts; CBVA – Chatbots and Voice Assistants; MarTech – Marketing Automation; DL/CNN/GAN – Deep Learning, Convolutional Neural Network, Generative Adversarial Network.

6.4.3 Step 3.3 of the methodology is implemented. Based on the frequency of mentions, context of use, user reactions, and impact on financial metrics, qualitative consequences are determined, and an assessment of identified positive and negative effects is performed (Table 9).

Table 9. Disruptive IT in Fashion E-commerce and their consequences (author's development)

№	Technology	Brief Description	Example of Application	Identified Consequences
1	AI	Recommendations, service automation	Amazon Fashion	+21% conversion, reduced marketing costs
	ML	Trend and demand forecasting	Shopify preference algorithms	More accurate forecasts, personalized marketing
2	AR / VR	Virtual try-on, 3D modeling	H&M AR fitting rooms	+75% positive reviews, increased traffic
3	Big Data / Analytics	Large-scale data analysis for decision-making	ASOS	-15% product returns
4	IoT / RFID	Product tracking, warehouse automation	Zara RFID chips	Reduced losses, optimized logistics
5	B&SC	Authentication, supply chain transparency	LVMH (AURA platform)	Increased trust, anti-counterfeiting
6	CBVA	24/7 customer service	Boohoo chatbots in messengers	Reduced support load, increased loyalty
7	MarTech	Digital tools for automated marketing and analytics	H&M, Zalando – email campaigns, lead generation	Increased ROI, better segmentation, relevant communications
8	DL/CNN/GAN	Deep neural networks for image processing, visual content generation	Nike – shoe design generation, virtual models	Rapid creation of trending products, reduced photography costs

To compare the impact of disruptive IT on digital transformation in Fashion E-commerce, key performance indicators (KPIs) were defined (Table 10).

Table 10. KPIs for comparing the impact of disruptive IT on digital transformation in Fashion E-commerce (author's development)

№	Disruptive IT	Key Performance Indicators (KPI)
1	AI/ML	Personalization level (%); Conversion rate (CVR); Order processing time; ROI from AI solutions
2	AR/VR	Number of virtual try-ons; Reduction in returns (%); User engagement rate
3	Big Data / Analytics	Accuracy of demand forecasting; ROI from analytics; CTR in personalized campaigns; Decision-making speed
4	IoT / RFID	Speed of logistics operations; Accuracy of product tracking; Warehouse cost reduction
5	B&SC	Time to verify product authenticity; Percentage of verified genuine products; Number of detected counterfeits
6	CBVA	Customer satisfaction (CSAT); Average response time; Share of inquiries resolved without human intervention
7	MarTech	CTR of campaigns; Conversion rate; Customer acquisition cost (CAC); ROI from marketing tools
8	DL/CNN/GAN	Quality of visual content (customer rating); Engagement with visual content; Time to create models

6.4.4 Based on content analysis of the representative sample, the consequences of disruptive IT were assessed using Maltego (Community Edition), and the results were visualized (Figure 1) [26].

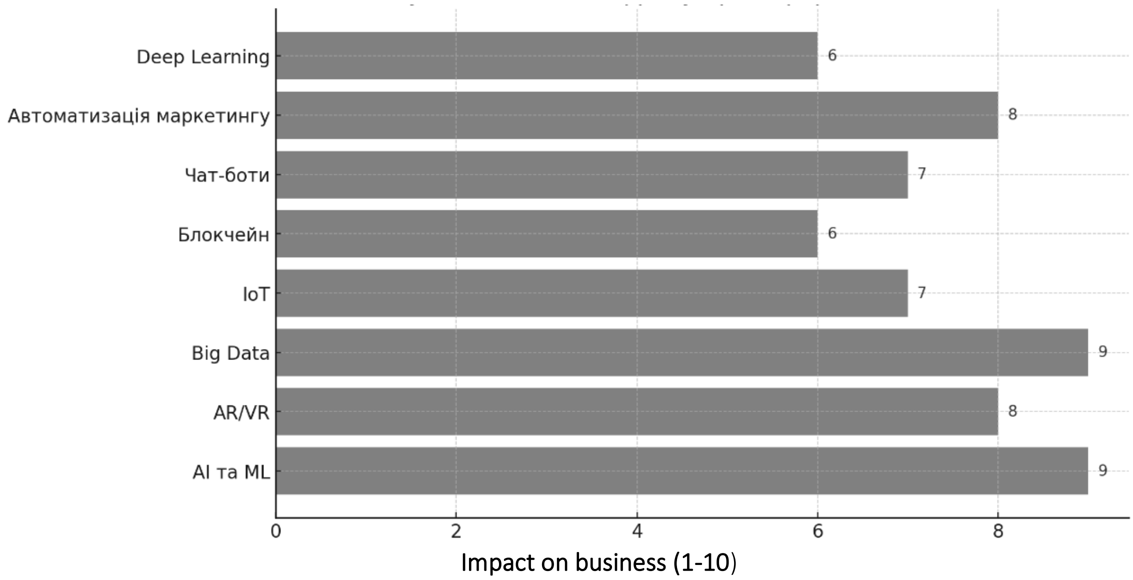

Fig. 1. Assessment of disruptive IT impact (author's development).

Figure 1 presents a graph illustrating the conditional assessment of the impact of major disruptive IT on digital transformation in Fashion E-commerce and their implementation priority. The impact scale ranges from 1 (low) to 10 (very high).

6.4.5 To confirm the hypothesis, practical examples of disruptive IT applications in Fashion E-commerce by real companies were collected (Table 11).

Table 11. Examples of real companies using disruptive IT in Fashion E-commerce (author's development)

Company	Technologies	Implementation Description
Zara (Inditex)	RFID (Radio-Frequency Identification)	• Product tracking in stores and warehouses; • Reduced losses and simplified inventory management
H&M	Big Data, AI (Artificial Intelligence)	• Personalized recommendations in the mobile app; • Assortment planning optimization
Nike	AR (Augmented Reality), NFT (Non-Fungible Tokens)	• Virtual shoe try-on via AR; • Creation of digital NFT collections
Amazon Fashion	Robotics, ML (Machine Learning)	• Logistics automation; • Forecasting product returns using machine learning models
LVMH	Blockchain	• Aura Blockchain Consortium platform for verifying the authenticity of luxury goods

The hypothesis is confirmed, as the list is complete, systematized, and validated across multiple independent sources.

7. Prospects for further research development

Successful implementation of disruptive IT in Fashion E-commerce requires combining technological tools with a deep understanding of consumer needs and market conditions. Future research could extend the analysis of disruptive IT consequences by incorporating additional sources (video analytics, open brand APIs), expanding temporal coverage, and integrating machine learning to automate OSINT data collection and analysis. Another promising direction is developing a dynamic model that allows real-time monitoring of technology impacts on consumer behavior.

8. Conclusions

1. The well-established scientific and practical knowledge has undergone further development. Results of a systematic analysis of contemporary scientific discourse have substantiated the presence and identified specific technologies that demonstrably constitute key factors influencing digital transformation in fashion e-commerce: AI/ML; AR/VR; Big Data/Analytics; Internet of Things/RFID; Blockchain & Supply Chain (B&SC); Content-Based Visual Analytics (CBVA); Marketing Technologies (MarTech); Deep Learning/Convolut.

2. For the first time, the authors have developed an impact matrix and graphical visualizations that demonstrate the varying influence of each technology on such domains as UX, logistics, and transparency. The identified impact factors are described, and their characteristics are defined.

9. Practical Significance

The findings of this research provide a structured and data-driven foundation for decision-making in the domain of digital transformation of Fashion E-commerce. The proposed impact matrix and visual representations of disruptive information technologies enable practitioners to identify, classify, and prioritize technologies according to their influence on critical business dimensions such as user experience, logistics optimization, and supply chain transparency. By integrating OSINT-based content analysis with managerial risk-assessment standards, the methodology offers a reliable tool for minimizing uncertainty in investment decisions, avoiding redundant expenditures, and improving the allocation of technological resources. The results may be directly applied by marketing specialists, IT managers, and strategic planners for developing innovative business models, forecasting consumer behavior, and enhancing customer engagement. Moreover, the approach contributes to the establishment of a replicable analytical framework that can be adapted across diverse market contexts, thereby ensuring both scalability and relevance in rapidly evolving digital ecosystems.

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