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Abstract. The purpose of the research is to develop an intelligent system able to support the design and management of a Customer Experience (CX) strategy based on the emotions tracked in real time at the different touchpoints in a store. The system aim is to make the shopping experience responsive to the customers' emotional state and behaviour and to suggest successful product/service design guidelines and customer experience (CX) management strategies whose implementation may affect current and future purchases. In this particular, the present paper focuses on the description of the integrate approach developed to design the overall CX and on the emotional recognition tools to elaborate the rich-data captured by a network of optical and audio sensors distributed within the shop.

Keywords: Customer Experience, Collaborative CX Design Approach, Emotional Recognition, Big Data.

1 Introduction

Retailers have begun to pay more and more attention to the design of experiential services to stimulate customer emotions and create unique experiences at shops [1]. This has determined a focus shift from the service design to the customer experience design [2] and led the retail to be considered not only as a market in which products are exhibited for sale but mainly as a space where events happen [3].

However, providing entertainment and organizing funny and creative events are not enough to ensure satisfactory Customer Experience (CX). Companies must manage all the clues they are sending to costumers according to a well-conceived and comprehensive CX strategy [4]. In general, the clues that may affect the customer experience are everywhere inside a shop (e.g., from the colors of walls to the lights, the odors and sounds of the store; the style of exhibitors; the uniform of shop assistants, etc.).

Current distributed networks of sensors and the availability of internet connections within shops, provide an interesting opportunity for retailers and for all CX stakeholders to observe what customers do, how they interact in the space and with the object populating it and with others and to understand what they feel, how they perceive the clues, which is their emotional state and why it changes if an incidental event occurs [5]. Such rich data represents a base:

1. To develop successful clues within the shops able to focus the customer attention and enjoy him/her;
2. To implement CX management strategies able to influence customer purchase probability [6], customer satisfaction [7] and customer loyalty [8];
3. To design improved visual merchandise and shop layout and finally,
4. To provide some drivers for the design of the offered product/service.

The emerging technologies for tracking customer behavior and emotion and the attention to CX challenge the way to design both product and services for retail [9] and highlight the needs for new tools able to collect raw data, arrange and represent such information based on the stakeholder work purpose and propose proper actions to make the shopping experience more engaging, the product more appealing, the services more responsive to the individual needs.

However, based on our knowledge, no study exploited intelligent system based on emotion recognition tools to monitor in real time the customer's experience along his/her journey and make the shopping experience responsive to the customers' emotional state and behaviour. Consequently, the introduction of systems based on affective computing is innovative in the CX research filed.

Starting from these general considerations, a long-term project, called EMOJ, has been launched in 2015 with the aim to answer to this challenging reality by reaching two main objectives as follows:

- Research and Modeling of a holistic approach to define the requirements for the development of every clue (i.e., product/service) which characterizes the store in a comprehensively way. The approach must embrace the holistic nature of CX, consider the unconscious needs of customers and of all process stakeholders and support the drawing of the customer journey and every touchpoint;
- Study and development of implement an intelligent system to support the definition, design and management of the CX strategy to make the shopping experience responsive in the various touchpoints based on the recognized customer's behavior and emotional state.

A significant step to reach the above-mentioned objectives is the definition of what CX is and how this definition impacts on traditional User-Centered design methodologies. The type and density of data necessary for customer analysis represent the starting point for the development of the supporting platform.

2 Customer Experience and Big Data Analytics: Main Challenges

1.1 The Design of Customer Experience

Customer Esperience can be defined as the person's response (internal and subjective) to all interactions (direct or indirect) with a company [10]. Such response is holistic in nature and is determined by customers' cognitive, affective emotional and social responses to the stimuli perceived during the interaction. In particular, CX is affected by all the product and services or clues with which customer get in contat along his/her journey [4]. If a company is able to corretly identify the touchpoints that most affect shopping experience and understand which stimulus they have to provide for ensure the best CX, depending on the nature of touchpoint in which the interaction takes place, it will be actually able to influence the customer in choose/repurchuase the products in a more profitable way.

However, despite many authors seem to agree on this perspective, no studies provide a holistic approach able to support the development of product and services in an integrated way, according to a determined CX strategy [11]. To support CX design, the well-known User-Centered Design (UCD) approach [12] seems to be suitable for the multidisciplinary disciplines it requires and for the methods and tools it proposes to ensure that products meet users' expectation. However, UCD focuses only on specific touchpoint (i.e., the product use), so that it lacks in consider all the interaction between the customer and the company. Moreover, it mainly focus on needs of particular customers (i.e., the users, the persons who effectively will use the product), so that it lacks in consider all stakeholders needs that the product must meet to ensure customer satisfaction in every stage of CX.

Finally, most of the reported studies in CX pointed out the importance to contract the emotional curve along the customer journey to measure the customer response and define each touchpoint design requirements [13, 14].

Today several methods and technologies allow the recognition of human emotions, which differ in level of intrusiveness. Obviously, the use of invasive instruments (e.g., ECG or EEG, biometric sensors) can affect the subjects' behavior and in particular it may adulterate his/her spontaneity and consequently the emotions experienced by them. The majority of such techniques, methods and tools refer to three research areas: facial emotion analysis [15], speech recognition [16] and biofeedback emotion analysis [17]. All techniques elaborate the data captured by a network of sensors embedded either in wearable systems or distributed in space and collected by data management systems as described in the following section.

1.2 Data-Rich Shop: An Opportunity for CX

Increasing availability of sensors and smart devices connected to the Internet, and powered by the pervasiveness of Cyber-Physical Systems and Internet of Things, create an exponential growth of available data. These advances are transforming traditional network application to be more human-centric [18]. We observe the hyper-connectivity of organizations, people, and machines taking us to data-rich environments and often facing big data challenges. All activities in the world, and everyday life of people, leave trails that can be accumulated on cloud-supported storage, while developments in open data movement contribute to the wide availability of such data. The key will be the introduction of sophisticated tagging algorithms that can analyze images either in real time when pictures are taken or uploaded from RGB-D sensors. To enable such evidence-based decision making, retailers need efficient processes to turn high volumes of fast-moving and diverse data into meaningful insights. The overall process of extracting insights from big data can be broken down into five stages formed by two main sub-processes: data management and analytics. Data management involves processes and supporting technologies to acquire and store data and to prepare and retrieve it for analysis. Analytics, on the other hand, refers to techniques used to analyze and acquire intelligence from big data. Thus, big data analytics can be viewed as a sub-process in the overall process of 'insight extraction' from big data. The data generated by RGB-D cameras in retail can be extracted for business intelligence. Currently, Big Data analytics is being applied at every stage of the retail process, working out what the popular products will be by predicting trends, forecasting where the demand will be for those products, optimizing pricing for a competitive edge, identifying the customers' attraction and working out the best way to approach them, for an optimization of CX strategy. For instance, retailers can collect demographic information about customers, such as age, gender, and ethnicity. Likewise, they can count the number of customers, measure the time they spend in the store, detect their movement patterns, measure their passing time in different areas, and monitor queues in real time. Valuable insights can be obtained by correlating this information with customer demographics to drive decisions for product placement, price, assortment optimization, promotion design, cross-selling, layout optimization, and staffing [19]. Another potential application of big data collection in retail lies in the study of buying behavior of groups. Among family members who shop together, only one interacts with the store at the cash register, causing the traditional systems to miss data on buying patterns of other members. Data from RGB-D sensors can help retailers address this missed opportunity by providing information about the size of the group, the group's demographics, and the individual members' buying behavior.

The customer-specific data can drive dynamic and personalized CX. By capturing important moments in the customer journey, and analyzing this customer-specific activity, retailers can help navigate customers through the ideal interaction points to reach desired outcomes. In this way, they can predict the products a customer will most likely be interested in and offer personalized options in real time across any number of channels.

2 CX Design Approach

The proposed approach to support Shopping Experience Design is characterized by a customer-centered iterative procedure consisting of the following five main activities:

5. Analysis of customers in the store: it implies the observation of behaviours of customer and the understanding of their emotional state during the interactions with products and staff. The results of the analysis can be represented through the construction of the customer journey map, which represents the main touchpoints in the store, and the creation of the emotional curve to graphically show the level of customers' satisfaction and to recognize which touchpoints need to be redesigned or adapted.
6. Planning of strategies to improve the shopping experience: definition of all changes to be applied to product and services and all strategical short-term and long-term actions that the company must implement in every touchpoint to maximize shopping experience.
7. Development of all intended products, services and clues for every critical touchpoint: the implementation of a CX strategy may imply the design of new products and/or services as so as the re-design of every product and service affecting each touchpoint.
8. Implementation of the prototypal CX strategy: introduction of prototypes of all products, services and clues along the customer journey to test the achieved CX performance
9. Testing and evaluation of resulted shopping experience: experimentation of the prototyped solution in real stores and measurement of customers' satisfaction to define possible improvements. Results of this activities include the elaboration of data collected through the construction of the emotional curve and guidelines to improve CX.

It is worth to notice how much strategic the analysis of the customer emotions, their mapping with his/her behaviour and the definition of related real time, short and long term actions are. For this purpose, a Knowledge-based System, which implements Machine Learning algorithms and Ontologies is defined and showed in Figure 1. The system can:

- Monitor the emotional state of customers along all the touchpoints that characterize the Customer Journey Map;
- Manage real-time actions to improve shopping experience;
- Support decision-making to define what are the most appropriate short and long term solutions to be adopted to improve the shopping experience.

3 A KB Platform to Support CX Management

The proposed knowledge-based system adopts two different strategies. On one hand, it acts directly on the shopping environment, surrounding the customer, to improve his/her buying experience in a reactive way. On the other hand, it provides a Decision Support System (DSS) able to help CX management in defining the optimal CX strategy and planning short and long-term actions. It requires the presence of a real time emotional recognition module to trace the customer emotional state in store.

The system exploits artificial intelligence algorithms (Machine Learning) based on inductive inference and makes decisions on the basis of logical rules derived from a knowledge framework composed by three main modules: the Service Ontology (SO), the Product Ontology (PO) and the Customer Ontology (CO).

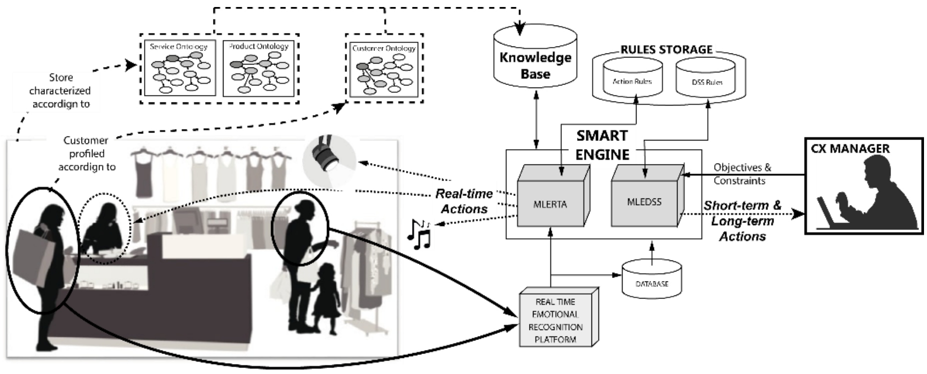

Fig. 1. The overall architecture of the KB platform

SO and PO allow the retailer's knowledge related to product/service to be mapped, structured and managed to design the service and product semantic model. UO provides semantic data structure related to the user characteristics and behavior. In this way, the knowledge necessary to manage the system reaction per emotions is defined through the relations among the entities of such ontologies, according to the results of psychological and marketing studies.

The core of the system is the Smart Engine (SE) that is characterized by two distinct modules: the Machine Learning Engine for Real-Time Actions (MLERTA) and Machine Learning Engine for DSS (MLEDSS). The SE takes its decisions based on the implemented Machine Learning algorithms, which implement logical rules of inference (e.g., Decision Trees algorithms, as the CART). A Knowledge Base module maps the information coming from the Smart Engine in a language (e.g., OWL) necessary to describe and implement the SO, PO and CO and to update them at scheduled times. Based on the contents of the Knowledge Base, the smart engine defines logical rules, in an "if-then" form, according to the relationships connecting the various entities of the Ontologies, and save them in a proper Rules Storage. Given the dual purpose of the platform, two kind of rules are defined: Action Rules and DSS rules. Action Rules aim to manage the system reactive behavior, through the changing of characteristics of service (e.g., number of opened counters) and products (e.g., the color of lighting) into the shop, according to the level of satisfaction experienced by the customers. In general, DSS rules allow the management of the behavior of the business strategy according to proper objectives and constraints. To define DSS rules the Ontology-Driven Business Rules technique can be used, to generate the enterprise model from the ontology domain [20]. To define Action Rules homogeneous or hybrid approaches can be used. Hybrid approaches are usually used to solve knowledge representation problems: they are based on models implemented through Answer Set Programming languages (e.g., AnsProlog) [21]. Homogeneous approaches, implemented by using SWRL language, allow to define logical rules just inside the Knowledge Base, using directly the OWL concepts [21].

Every time the Smart Engine receives data in input, coming from the emotional recognition platform (e.g., a specific emotional curve in a specific touchpoint), it takes a decision based on the corresponding Action Rule and activates the proper service and product reactions (e.g., providing personalized offers for a specific customer, changing the music genre in the shop, etc.).

At the same time, all input data are stored in a Database in order to enable statistics elaborations. Based on the resulting statistical data, the DSS tool, provide to the CX manager some suggestions on possible actions to improve planning of a CX Strategy, according to pre-defined objectives and constraints.

2.1 The Emotional Recognition and Analytics Module

The proposed tool is composed by four modules (Figure 2). The first module provides person identification whenever he/she is detected in the proximity of a Touchpoint. The other three modules allow to acquire and analyze emotional information. Each of them is design to work as a standalone tool, so that the functionality of system is not compromised when the others are missing. They are as follows: Facial expression recognition, Speech recognition and the Biofeedback analysis modules.

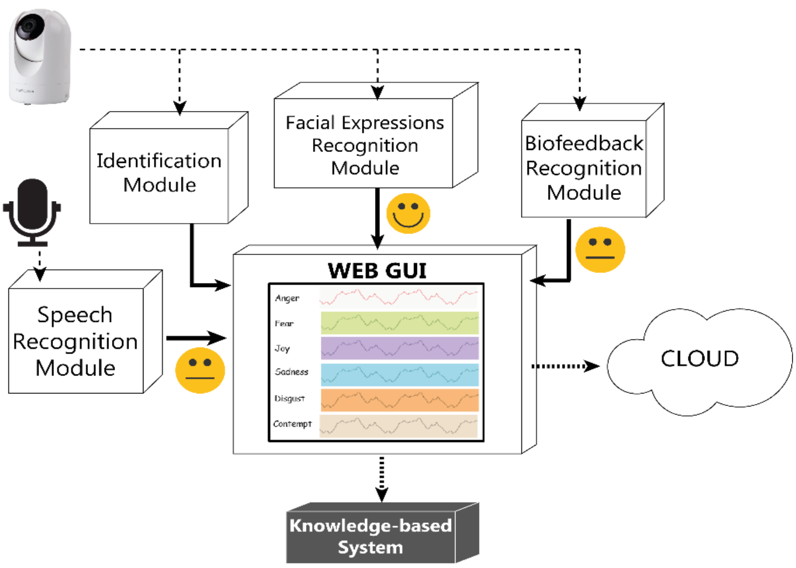

Fig. 2. The Architecture of the proposed Real Time Emotional recognition platform

The facial expression recognition module makes use of IP Wi-Fi full-HD cameras equipped with PTZ technology with autofocus. Each camera is installed in correspondence of every Touchpoint and continuously sends the video streams to the central server, which processes every video frame and returns the measure of the customer's emotions. This module embeds the Affectiva opensource engine Affdex [22], that provides in output a percentage value associated to the intensity of the main Ekman's emotions (i.e., Joy, Sadness, Anger, Fear, Contempt, Disgust and Surprise). Moreover, it provides measures for the Engagement (i.e., the measure of how the subject is "engaged") and the Valence, which gives a measure of positivity and negativity of the experience. The Speech recognition module refers to speech samples collected during organized surveys, or recorded from microphones installed in every Touchpoint. Also in this case, our software will be integrated with an already existing emotion recognition engine. At the time the research is focused on the evaluation of the most reliable algorithms to process voice parameters.

Several tools can be used depending on the speech analysis approach we want to adopt. For example, it is possible to use Google APIto convert the human voice in written text, and the IBM Watson software, for the text emotional analysis. Otherwise, we can adopt the AudioProfiling tool to directly extract emotions from the voice features (i.e., Loudness, Articulation, Time, Rhythm, Melody and Timbre). The third module allows the biometric data analysis through the acquisition of heartbeat and/or breath rate. Such bio-information are usually monitored by using intrusive sensors (e.g., ECG). However, VPGLIB (ex QPULSECAPTURE) is used to monitor such parameters in a non-intrusive way. The application is an OpenCV extension library that uses digital image processing to extract the blood pulse rate and provides an estimation of breath frequency from the video of the human face. In this way it is possible to acquire the breath rate and heartbeat of the person through the same camera used for facial recognition, with an absolute error in most cases less than 5 bpm. The next step is to trace these measurements to the emotional percentage values (Joy, Anger etc.). In fact, it has been demonstrated that exists a correlation between these measurements and the emotional state [17]. To this purpose, the APIs available by SensauraTech is adopted.

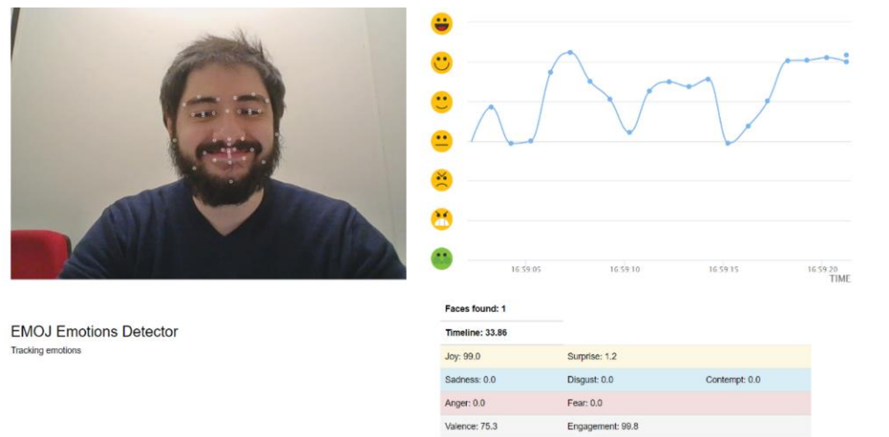

Fig. 3. The user interface of the emotional recognition module

To ensure the customer identification in each touchpoint, the Identification Module implements a face recognition engine that uses a database of previously stored images (e.g., such images can be collected during the customer registration required for loyalty card).

In this way, the customer is identified every time that he/she passes in from of a camera. Face Recognition APIs, from Lambda Lab allow to obtain this purpose.

A web GUI displays the data provided in output by emotional recognition platform. Such interface provides a representation of the customers emotional curve as a function of the Time and of the Valence values, measured on a scale that goes from -100 to 100. Moreover, it displays the percentages related to the primary emotions. Real time data related to each touchpoint can be plotted for one or more customers. In this last case, average values are provided.

The analytics module is based on the information provided by the previously described system and is a cloud based infrastructure previously designed for intelligent retail environments [22, 23] and used also in this project. The tool aims to analyze big data coming from massive customer emotions mining along with the customer journey in a pervasive computing scenario. The analytics module architecture describes the policy used, from the beginning of the project. The system main aspects are the data and the cloud.:

The Data are sent, in real time, to server by string or JSON form. Strings are sent in a queue URL using HTTPSv protocol. HTTPS (also called HTTP over TLS, HTTP over SSL, and HTTP Secure) is a protocol for secure communication over a computer network which is widely used on the Internet. HTTPS consists of communication over Hypertext Transfer Protocol (HTTP) within a connection encrypted by Transport Layer Security or its predecessor, Secure Sockets Layer. The main motivation for HTTPS is authentication of the visited website and protection of the privacy and integrity of the exchanged data.

In its popular deployment on the internet, HTTPS provides authentication of the website and associated web server with which one is communicating, which protects against man-in-the-middle attacks. Additionally, it provides bidirectional encryption of communications between a client and server, which protects against eavesdropping and tampering with and/or forging the contents of the communication. HTTPS is especially important to avoid anyone on the same local network can packet sniff and discover sensitive information.

In the project Amazon Web Services (AWS) cloud service is used. AWS, is a collection of cloud computing services that make up the on-demand computing platform offered by Amazon.com. Cloud computing exhibits the following key characteristics:

- Agility. It improves with users' ability to re-provision technological infrastructure resources.
- Cost reductions claimed by cloud providers. A public-cloud delivery model converts capital expenditure to operational expenditure. This purportedly lowers barriers to entry, as infrastructure is typically provided by a third party and need not be purchased for one-time or infrequent intensive computing tasks. Pricing on a utility

computing basis is fine-grained, with usage-based options and fewer IT skills are required for implementation (in-house).

- Device and location independence that enable users to access systems using a web browser regardless of their location or what device they use (e.g., PC, mobile phone). As infrastructure is off-site (typically provided by a third-party) and accessed via the Internet, users can connect from anywhere.
- Maintenance of cloud computing applications that is easier, because it does not need to be installed on each user's computer and can be accessed from different places.
- Multitenancy that enables sharing of resources and costs across a large pool of users, increases of peak-load capacity (users do need not to be engineers), utilization and efficiency improvements.
- Productivity that may be increased when multiple users can work on the same data simultaneously, rather than waiting for it to be saved and emailed. Time may be saved as information does not need to be re-entered when fields are matched, nor do users need to install application software upgrades to their computer.
- Reliability improving with the use of multiple redundant sites, which makes well-designed cloud computing suitable for business continuity and disaster recovery.
- Scalability and elasticity via dynamic ("on-demand") provisioning of resources on a fine-grained, self-service basis in near real-time (Note, the VM startup time varies by VM type, location, OS and cloud providers), without users having to engineer for peak loads. This gives the ability to scale up when the usage need increases or down if resources are not being used.
- Security that is improved due to centralization of data and resources, etc., but sometimes there can be a loss of control over certain sensitive data, and the lack of security for stored kernels. However, the complexity of security is greatly increased when data is distributed over a wider area or over a greater number of devices, as well as in multi-tenant systems shared by unrelated users. In addition, user access to security audit logs may be difficult or impossible.

5 Conclusion

The present paper introduced an approach, based on a customer-centered process to support the achievement of a completely satisfying customer experience in a retail context. Such approach aims to support the definition of requirements and drive the development of every clue (i.e., product/service) which characterizes the store in a comprehensively way. A prototypal Knowledge-based system to analyze the emotions experienced by every customer in every touchpoint is here described. It implements Machine Learning algorithms and Ontologies.

In the context of retail, such system introduces several innovations:

- Monitoring of real customer experience in an automatic way along all the touchpoints: the system implements an innovate Real-time Emotional Recognition Platform able to monitor customers in a non-intrusive way. Consequently, the system will be able to provide to the company an enormous amount of data about consumers (including spontaneous emotions) that so far has never been possible to collect with traditional ethnographic techniques. In particular, the use of this technology will allows to have a more elaborate customer profile than that obtainable from simple personal data or from surveys, and will make possible to propose customizable offers.

- Automatic management of the shop environment based on machine learning: for the first time an automation system, responsive to customer emotions, is introduces in a retail context.
- Decision Support System based on customers' emotions: traditional DSS lack to consider the impact of management decisions on customer's emotions.

The proposed Real-time Emotional Recognition and Analytics Platform, compared to the most common tools and methods applied for emotional recognition and analysis, presents the following advantages:

- Not invasive solution that integrate several technologies: the presented tool will allow monitoring the emotive status of customers without being aware of it (although, for privacy issues, they should be informed that they are monitoring). Moreover, it exploits several tools and method of emotional recognition; it will be able to provide data that are more reliable that any other existing system.
- Totally modular architecture: each technology used for emotional recognition constitute an independent module. In this way, each module can work as a standalone tool, so that the functionality of system is not compromised when the others are missing.
- Web-based user-interface: easily and remotely accessible (protected by security protocols). In this way, the user can access data in a cloud-based environment.
- Emotion recognition technology inserted in a Customer Experience context, a totally innovative element

The introduction of this system in retail environments can result in important benefits. However, its implementation in practical context will require a lot of other research. The platform for the recognition of emotions still requires testing to verify its effectiveness in the various possible operating conditions (e.g., changing light conditions, noise, various number of customers present in the store). It will also be necessary to define a model for the analysis of data from the various tools and test it through appropriate training set. Finally, several future studies will be needed to define the KB implemented by the proposed knowledge-based system and define the solutions that must be adopted for the implementation of the Smart Engine.

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