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Abstract

Purpose – The purpose of this paper is to quantify external and internal uncertainties in product design process. The research addresses the measure of product future changes.

Design/methodology/approach – Two methods are proposed to model and quantify uncertainty in the product life cycle. Changes of user preferences are considered as the external uncertainty. Changes stemming from dependencies between components are addressed as the internal uncertainty. Both methods use developed mechanisms to capture and treat changes of user preferences. An agent-based model is developed to simulate sociotechnical events in the product life cycle for the external uncertainty. An innovative application of Big Data Analytics (BDA) is proposed to evaluate the external and internal uncertainties in product design. The methods can identify the most affected product components under uncertainty.

Findings – The results show that the proposed method could identify product changes during its life cycle, particularly using the proposed BDA method.

Practical implications – It is essential for manufacturers in the competitive market to know their product changes under uncertainty. Proposed methods have potential to optimize design parameters in complex environments.

Originality/value – This research bridges the gap of literature in the accurate estimation of uncertainty. The research integrates the change prediction and change transferring, applies data management methods innovatively, and utilizes the proposed methods practically.

Keywords Product design, Big data analytics, Agent-based modelling, Uncertainty quantification

Paper type Research paper

1. Introduction

A product life cycle includes several stages from intangible conceptual design to used product at the end of its life time. Managing the product life cycle requires finding solutions for uncertain changes and unpredicted events. Studies showed that more than half of initial user requirements will be changed before a project completion (Kobayashi and Maekawa, 2001; Ramzan and Ikram, 2005). Improper management of requirement changes imposes negative consequences to a system or product such as increased complexity (Chen, 2006), data loss (Morkos *et al.*, 2010), and wasted time and money (Morkos and Summers, 2010; Morkos *et al.*, 2012). However, if probable changes and uncertainties are predicted in advance, the chance of design fail (e.g. customer's dissatisfaction) can be reduced. Therefore, it is essential to evaluate uncertainties in the product life cycle.

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Uncertainty is inevitable in engineering systems. Any lack of data or lack of trust in identified customers' needs is considered as uncertainty (Wynn *et al.*, 2011; Afshari and Peng, 2014). The research (Eckert *et al.*, 2009) showed that "customers' need" is a dominant driver of changes in the product life cycle. Uncertainty in the customer need affects the design solution. Customers may update their needs and preferences during the product life time. Such uncertainty affects product development (PD) in term of cost, adaptability, and time.

It is proved that decisions in the design stage contribute to 70-85 percent of the total product cost (Ullman, 1997; Besterfield *et al.*, 1995; Cao *et al.*, 2008). In terms of sustainability, these decisions would impact 80-90 percent of the final performance of a product during its life cycle (May *et al.*, 2012). Therefore, if a designer could identify future changes of a product in the design stage, a proper decision can be made to minimize cost and environmental impacts of the product. Hypothetically, effects of the design stage decisions can be extended to other measures and indexes (e.g. product quality, durability, adaptability, etc.).

The existing research methods in the product change mainly study the propagation of changes into product components and functions. In other words, the propagation of changes within product structure is discussed regardless of the source of changes (e.g. Martin and Ishii, 2002; Yang *et al.*, 2014). The change of customers' preference in a product life cycle is a significant uncertainty for product design. Despite the variety, current qualitative and quantitative methods for the change of preferences (e.g. interview with customers and experts, questionnaires, QFD, marketing research, and engineering methods) have limitations. For example, the change propagation methods do not provide a metric for comparing design alternatives in different scenarios. Thus, two methods are proposed in this research to bridge the gap of literature. Both methods use innovative mechanisms to capture and transfer changes into the product design.

The goal of this research is to quantify the changes of customers' preferences during the life time of a product. By quantifying the changes, a designer will be able to provide appropriate solutions in product design stage. The research question proposed in this paper is to find ways to measure future changes of customers' needs in the design stage. If the quantified changes of customers' preferences are provided to designers, product components to meet functional requirements (FRs) and design parameters related to the changes can be considered to meet the changing need.

The proposed agent-based model (ABM) simulates changing events and interactions in a product life cycle. An ABM consists of a set of elements (agents) characterized by some attributes to interact each other through defined rules in a given environment. The Big Data method is proposed for further improvements of the presented ABM in term of social and technical factors, and the study scope. Big Data improves deficiency of other methods to quantify external and internal uncertainties in the product design process. In other words, Big Data analytics (BDA) uses real data instead of predicted or simulated data in other methods. Big Data is a buzz word used in academia and industries recently. The application of the Big Data is growing for the better data-driven decision making (Obitko *et al.*, 2013). The Big Data provides a cost-effective way to obtain users' information for a knowledge economy. As a result of the age of information, a lot of user and product data are available in the internet for analysis of the interaction between users and producers. Using BDA, product and user data can be easily collected to be used for product improvement. Among discussed types of BDA including descriptive, predictive, and prescriptive data analysis, this research develops a prescriptive analytics for product design process. In this type of BDA, not only past trends are used to mine user data (descriptive analysis), the future trends are also predicted (predictive analysis). Solutions for product design based on effects analysis are then proposed. Therefore, the BDA method is presented to enrich the ABM for the measurement of future product changes in the product life time. The efficiency of methods is justified based on the convergence of predicted changes to the real changes of a product.

The related research is discussed in next section. In the methodology section, the proposed methods to quantify changes in a product are explained in detail. Each method is then validated using the product example in the case study section. The detail is discussed in Section 5 for the sensitivity analysis and parameters setting. Finally, the research is concluded with main findings and future research directions.

2. Literature review

This section reviews methods to model and measure uncertainties in PD process in order to highlight compatible methods for studying customers' preference changes.

2.1 Change propagation approaches

Risk, change, and uncertainty are considered as important issues in product design (Pahl and Beitz, 1996; Ulrich and Eppinger, 1995). Methods have been proposed to model and evaluate the effects of changes in products. Initially, these approaches were proposed to only measure changes in product applications (Marca and McGowan, 1988; Belhe and Kusiak, 1995). These methods were then extended to integrate the change quantification within the PD process as discussed in this section.

The design structure matrix (DSM) is a method to efficiently represent elements of a system and their interactions (Steward, 1981). The basic DSM approach organizes complex development projects by determining a sensible sequence of tasks being modeled (Yassine and Braha, 2003). The DSM captures existence and strength of an interaction between design tasks or parts of a product (Eppinger and Browning, 2012). Several extensions of the DSM have been proposed to determine design priority and to minimize redesign time and iterations in concurrent engineering (Yassine and Braha, 2003; Yassine and Sreenivas, 2008). Wei *et al.* (2001) proposed a component-based DSM method to arrange high-interactive components of a product in clusters. Luh *et al.* (2011) proposed a method to develop multiple products for different markets based on a quantified DSM. Using informational structure perspective, design priorities are optimized to manage product variety. Yang *et al.* (2014) developed an overlapping-based DSM to measure the interaction strength for clustering components in PD projects. Evolution DSM and sensitivity design structure matrix (sDSM) measure the strength of interaction between teams performing overlapped activities. Despite the extensive application of DSM in product design, the external uncertainty is not modeled in the proposed methods.

Change propagation approaches study effects of contextual changes on the internal structure and components of a product (Eckert *et al.*, 2004). Design for variety (DFV) methodology finds the possible changes of product needs or customers' preferences and helps designers to reduce the impact of variety in the life cycle costs of a product (Martin and Ishii, 2002). The method quantifies the magnitude of change in components of a product to meet the future market requirements using Generational Variety Index (GVI). Coupling Index is then used to measure internal effects of the change propagation into other product components. Suh *et al.* (2007) proposed Change Propagation Index (CPI) to measure total changes propagating out of the components minus the changes coming into the components. sDSM, introduced by Kalligeros (2006), identifies design variables with the most sensitivity to changes; a designer could insert flexibility to these highlighted subsystems or components. Giffin *et al.* (2008) suggested a normalized CPI to compare sensitive components in each design scenario. However, the approach lacks defining the magnitude of changes in the multi-domain analysis.

Change prediction method (CPM), developed by Clarkson *et al.* (2004), measures the risk of change propagation between components using DSM. The output of CPM is a DSM including the values for combined (direct and indirect) risk of the change propagation. Ariyo *et al.* (2008) improved the CPM by proposing a hierarchical aggregation method. The method could predict the risk across multiple levels including components, systems, and product. Koh *et al.* (2012) presented a model to predict and manage undesired engineering change propagation during the development of a complex product. House of quality (HoQ) and the CPM are the basis of the proposed method. The method can assess change options during engineering changes. Hamraz *et al.* (2012a) proposed a matrix-based algorithm to facilitate the model's calculations with spreadsheet programs. The suggested technique accounts for multiple changes at a time. Several developments have been presented to the basic CPM (Hamraz *et al.*, 2012b, 2013; Ahmad *et al.*, 2013) to enrich the method with a better prediction and change propagation measurements. The most recent extension is proposed by Hamraz and Clarkson (2015) that links the CPM with function-behavior-structure linkage method. The method provides details in modeling and analysis of engineering changes.

2.2 ABMs

ABMs or multi-agent systems (MAS) provide an effective approach to solve problems with the large size of the domain and frequently changing structure (Barbati *et al.*, 2012). Reviewing ABMs, there are limited applications in design fields compared to other areas. ABMs are mainly developed in the modular and collaborative design of products (Jinfei *et al.*, 2014). The purpose of collaborative design is to meet customers' requirements using the collaboration of researchers from different disciplines. MAS provide a structure to contribute designers' ideas in a collaborative fashion. Ostrosi *et al.* (2012) applied agent-based modeling to model product families in the conceptual design. The proposed approach envisions the configuration of product as a structural and collaborative design problem; different actors can be included in agent-based modeling. The final output of the model is a set of optimal product configurations. Cao *et al.* (2008) proposed an agent-based approach for the conceptual design of mechanical products. The approach applied an agent-based structure to map behavioral and functional matrixes. A design flow proposed by Xu *et al.* (2008) customized products using the similarity evaluation. The method combines the analysis of customer's requirements using QFD with MAS to optimize decisions. Zhang and Kimura (2005) proposed an agent-based method to analyze assembly methods and assembly sequence of components. Rai and Allada (2003) proposed a two-step approach for the modular product family design. A multi-objective optimization using multi-agent framework first determines an optimized set of modules. A post-optimization then analyzes the quality loss function of each module. Other research in applications of ABM for the robust product design mostly focussed on collaborative solutions (Huang *et al.*, 2000; Liang and Huang, 2002; Jia *et al.*, 2004; Chen *et al.*, 2014). Maisenbacher *et al.* (2014) applied agent-based modeling to support the product-service system development. The research highlighted the dynamic structure of the simulation within ABM which enables the uncertainty analysis. Thus, ABM has a great potential to help designers to model uncertainty in PD.

2.3 Big Data methods

Applications of data-centric approaches such as Big Data and business analytics have been tremendously increased recently (Lavalle *et al.*, 2011; Chen *et al.*, 2012; Buhl *et al.*, 2013). Pattern recognition, machine learning, data mining, and BDA are some tools and approaches widely used in industries and organizations. To obtain the advantages of data-centric approaches, organizations require a good understanding of how the methods should be utilized in different decision process contexts (Davenport, 2010; Işik *et al.*, 2013). The study by Tien (2013) recommends four steps or components to Big Data processing including: acquisition (data capturing), access (data indexing, storing, sharing, and achieving), analytics (data analysis and manipulation), and application (data publication). Huge popularity and applications of social networks have motivated companies to focus on social or commerce mining. Analysis of customer behavior, opinion mining, user relationship mining and clustering, and sales prediction are of growing research topics in industries (Chon *et al.*, 2006; Al-Noukari and Al-Hussan, 2008; Cohen *et al.*, 2009; Provost and Fawcett, 2013). Some applications include using customer relationship mining to formulate proper strategies for managing customer demands (Lam *et al.*, 2014), and the online opinion analytical framework to detect weaknesses of a product (Wang and Wang, 2014).

Despite the benefits and potentials of using Big Data, limited studies were found to apply BDA for the uncertainty quantification in product life time. Dutta and Bose (2015) proposed a framework to implement Big Data projects in manufacturing. The framework consists of three main stages including strategic ground work, data analytics, and implementation. An application of the proposed framework in a cement manufacturing corporation showed that clear understanding of the problem, management support, cross-functional teams, and culture of data-driven decision making is necessary for the success in Big Data projects. Van Horn *et al.* (2012) reviewed methods and applications to use Big Data in early, middle, and late stages of product design phase. They proposed design analytics (DA) as a paradigm to transform customer data into design knowledge. The DA includes capturing, storing, and leveraging digital information about a product and its performance and usage. The model was used to improve the performance of a product. Other methods proposed for BDA in the product life cycle (Cooper *et al.*, 2013; Rohleder *et al.*, 2014) lacks applications.

Within factory and industrial environments, machine-generated data are used for predictive manufacturing systems. Therefore, machines and systems are enabled with "self-aware" capabilities such as predictive maintenance systems (Lee *et al.*, 2013). Considering limitations in the research for applying reliability concepts in BDA (Lee *et al.*, 2014; Meeker and Hong, 2014), it is suggested to improve reliability and minimize uncertainty in Big Data applications for the entire product life cycle as the future research.

2.4 Summary of literature

The literature in predicting changes during the product life cycle and transferring the changes into the PD process is summarized in Table I. Ten criteria are considered to evaluate the literature. These criteria are based on requirements in change prediction modeling addressed in literature. Considering a "change prediction method" as a system, we divide criteria into input, process, and output to highlight the literature gaps.

DSM-based methods and CPM-based methods have problems in the lack of integrating the change prediction within change modeling methods. In other words, these methods mostly evaluate the internal effects of changes in the model, while external changes are qualitatively considered. Therefore, integrated methods to predict

Table I. Summary of specifications for reviewed engineering change prediction methods

Criteria		DSM[a]-based methods		CPM[b]-based methods		Agent-based models		Big Data-based models	
		Basic model	Extensions	Basic model	Extensions	Literature	This paper	Literature	This paper
Input	Integrated measurement of external uncertainty		✓				✓		✓
	Considering variety of values and magnitudes of changes				✓	✓	✓		✓
	Objective input parameters				✓	✓	✓	✓	✓
	Evaluating sociotechnical uncertainty and events		✓			✓	✓		✓
Process	Considering dependencies between components	✓		✓			✓		✓
	Dynamic method to update effects of changes				✓	✓	✓	✓	✓
	Evaluating changes in various periods of PLC[c]						✓	✓	✓
Output	Transferring uncertainty into components, functions, and DPs[d]		✓	✓		✓	✓		✓
	Ability of implementing on redesign process	✓		✓		✓	✓		✓
	Ranking of design alternatives		✓		✓	✓	✓	✓	✓
Advantages		Easy implementation		Quantifying components dependencies		Prediction of external changes		Accurate evaluation of changes	
Disadvantages		Weak to evaluate multiple changes		Weak to evaluate external changes		Dependence on developed model parameters		Limitation to access data	

Notes: [a]DSM, design structure matrix; [b]CPM, change propagation method; [c]PLC, product life cycle; [d]DPs, design parameters. ✓ in this table show the existence of defined criteria for each method. Thus, it is a 0-1 table and ✓ represent 1 and to evaluate changes are required. Reviewed ABM methods and Big Data-based methods have shown the better compatibility with defined criteria. However, a comprehensive model is needed to meet all the criteria.

3. Methodology

Eckert *et al.* (2009) recommended two main approaches for changes in the PD processes: approaches focussing on the early design process (to anticipate the need for changes), and methods to predict the impact of changes. We followed this recommendation to bridge the gaps of the literature. Hence, two methods are proposed to predict changes and to transfer the changes into the PD process. Both methods consist of modules for the change prediction and change transferring.

3.1 Agent-based modeling for the prediction and transferring changes into the PD

A model is extended based on the diffusion theory (Bass, 1969) and the prediction of changes of customers' preferences (Afshari *et al.*, 2013). The model addresses needs for the quantification and transferring changes into the PD as shown in Figure 1. The model has multi-domain (social and technical elements embedded), scenario-enabled, and customer-oriented features.

The model consists of five processes including QFD survey, data mining, ABM, internal evaluation, and change evaluation as shown in Figure 1. A product is first decomposed into its components and subsystems. The list of product components is used to define a QFD survey. In addition, other decisions such as the scope of study, market, and details of the product specifications are necessary to initiate the model. Using an initial HoQ in the QFD technique, collected customers' preferences are transferred into engineering specifications (FRs). The FRs are then mapped into product functional parts and subsystems. These mapping matrices (customers' preferences into FRs, and FRs into parts and subsystems) are essential to measure the parameters in next steps as presented in the Appendix.

Data mining is an important step in the proposed model. Some tools and analyses such as statistical analysis, prediction methods, quantitative and qualitative data collection methods, etc., are used to estimate the value of parameters. Trends in the technology evolution are estimated for the list of components and subsystems. Using retrospective data or consulting with experts and manufacturers are two common methods for the quantitative trend estimation.

The collected data are applied to simulate a product life cycle using agent-based modeling. Ability of ABMs to simulate multiple interactions of agents in complex systems is used to model and quantify effects of external changes on customers' preferences. A process of agent-based modeling is presented in Figure 2.

For ABM, research questions, scope, and objectives of the simulation should be defined. The collected data are used to define required parameters, variables, and

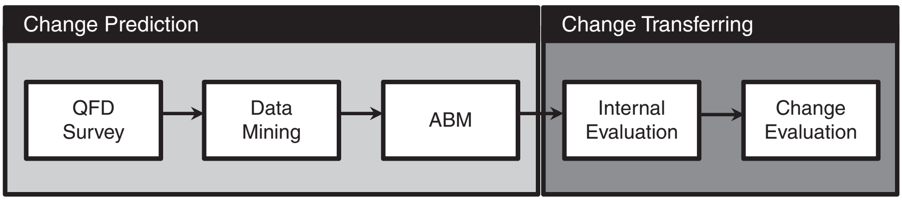


Figure 1. Schematic of the proposed agent-based model (ABM)

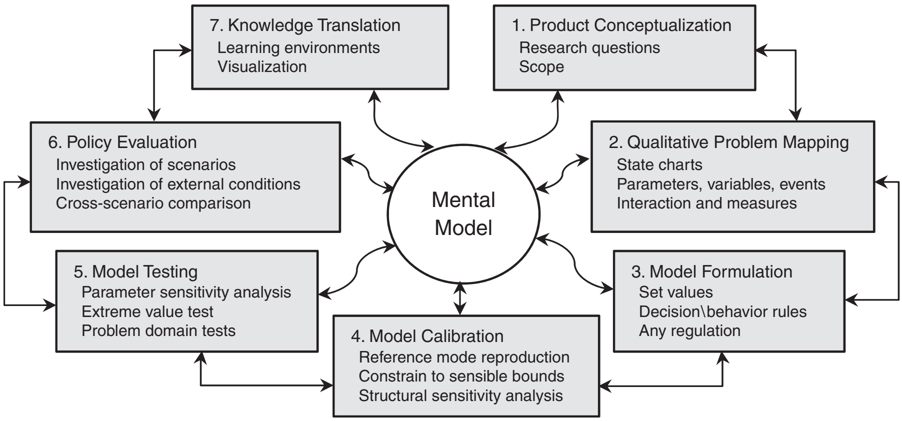


Figure 2.
Process of agent-based modeling

interactions in the model. Events and specific regulations are then modeled. The rest of steps for agent-based modeling are discussed using a product.

Figure 3 presents a schematic view of interactions in the proposed model. The model quantifies the interaction of customer to customer, and customer to technology as shown with 1 and 2 in Figure 3.

It is proved that exploring user's perception and the adoption for a specific product is useful for understanding the design of product features (Tsai and Ho, 2013). The basis of ABM is an extended version of basic diffusion theory shown in Equation (1). The aim is to evaluate the effects of social interactions and mass media on people's preferences when such changes of preferences matters for a manufacturer:

$$\frac{dY(t)}{dt} = m \cdot \left[\overline{Y} - Y(t)\right] + n \cdot \frac{Y(t)}{\overline{Y}} \cdot \left[\overline{Y} - Y(t)\right] \tag{1}$$

In Equation (1), $Y(t)$ is the total number of customers who adopt new products at time t, $\overline{Y}$, the total number of potential adopters, the coefficient m, the share of innovation (hence, first part of the equation shows the leading customers who buy a new product

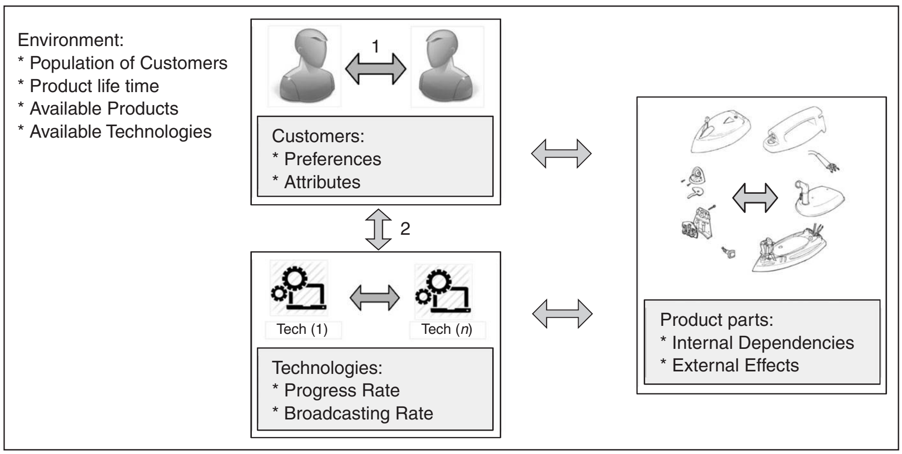


Figure 3.
Schematic view of elements and interactions in the proposed agent-based model

without the influence of others), the coefficient n represents the share of imitation (second part of Equation (1) shows the people who buy new product influenced by others). To propose a mathematical formulation for the changes in customers' preferences, events affecting the preferences are identified. Technology improvements and people interactions are considered as two major events invoking uncertainty into the model. It is considered that people interaction happens more often than the technology improvement (assuming people interaction and technology evolution events to occur in period t and P, respectively, $t < P$). Figure 4 depicts the events affecting customers' preferences in a product life cycle.

At $t = P_1$, two different events affect the preferences. The first event is the accumulation of interactions between customers, and the second event is the broadcasting and adoption of new technology by leading customers. Equations (2) and (3) formulate the events:

$$CP_{i,j}(t_n) = \sum_{t=1}^{t_n} \gamma_{frd}(i,j,t) \cdot \left[(1-\omega_{frd})CP_{i,j}(t-1) + \omega_{frd} \cdot P_{frd}\right] + \left(1-\gamma_{frd}(i,j,t)\right) \cdot CP_{i,j}(t-1) \quad (2)$$

$$CP_{i,j}(Pr_1) = \varphi_{tech}(i,j,P_1) \cdot \left[(1-\omega_{tech})CP_{i,j}(t_n) + \omega_{tech} \cdot P_{tech}\right] + \left(1-\varphi_{tech}(i,j,P_1)\right) \cdot CP_{i,j}(t_n) \quad (3)$$

A customer (i) is autonomous to adopt a new technology for component (j) in interactions with their friends; the probability of adoption from friends (γ_{frd} (i, j, t)) is defined using Bernoulli distribution with $p = 0.5$. At the end of a product life cycle, mutual effects of both events are measured using Equation (4):

$$CP_{i,j} = \sum_{t=t1}^{T} \varphi_{tech}(i,j,P_m) \cdot \left[(1-\omega_{tech})CP_{i,j}(P_m) + \omega_{tech} \cdot R_{tech}(j)\right] + \left(1-\varphi_{tech}(i,j,P_m)\right) \cdot CP_{i,j}(P_m) \quad (4)$$

In Equation (4), I refers to the set of customers ($i \in I$), J stands for the set of product parts and components ($j \in J$), and T defines the time of events ($t \in P$) and ($P \in T$). The rest of parameters and variables are as follows.

$CP_{i,\,j}(t)$ is the preference of customer i for part j at time t; γ_{frd} (i, j, t), the adoption probability of customer i for part j at time t when interacting with a leading friend; ω_{frd}, the weight of imitation (inspired by friends) in adopting a new technology; P_{frd}, the

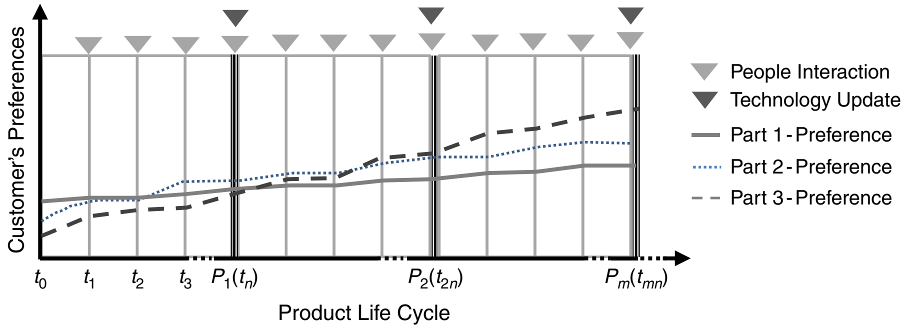


Figure 4. Summary of events affecting customer`s preferences in product life cycle

technology preference of a friend; $\varphi_{tech}(i, j, p)$, the adoption probability of customer i for part j at time t a new technology is introduced; ω_{tech}, the weight of innovation (inspired by media) in adopting a new technology; $R_{tech}(j)$, the rate of technology improvement for each part; and $\overline{CP_j}$, the average customers' preference for part j.

The customer's preferences are used to measure average part's preferences at the end of the product life cycle using Equation (5):

$$\overline{CP_j} = \sum_{i=1}^{I} CP_{i,j}/I \text{ for } j \in J \tag{5}$$

For a large population of customers, it is difficult to run the explained measurements in Equations (2)-(5). Hence, interactions are modeled using software packages. Table II summarizes the required attributes in the proposed ABM. The elements introduced in Table II are used to simulate interactions and influences of agents and environments during a product life time.

The output of agent-based modeling is the quantified value of changes in customers' preferences affected by interactions. The changes in customers' preferences are transferred into product components. The magnitude of changes for each product component and subsystem are measured. This is considered as the end of the change prediction for studying external elements of the product structure.

Transferring external changes into product components is the next step to evaluate interdependencies between components. Two items are considered: the magnitude of changes which is the output of the ABM, and the dependencies between parts to evaluate the internal effects. Hence, a new matrix is defined to elicit the dependencies between parts. Assuming INT as the dependency matrix between n part, and vector MAG as the magnitude of changes transferred to product parts from external interactions during a product life cycle, vector CHG is evaluated as the total changes transferred into all parts and components of a product as shown in Equations (6) and (7):

$$CHG = INT \times MAG \tag{6}$$

$$\begin{bmatrix} CHG_1 \\ \vdots \\ CHG_n \end{bmatrix} = \begin{bmatrix} INT_{1,1} & \cdots & INT_{1,n} \\ \vdots & \ddots & \vdots \\ INT_{n,1} & \cdots & INT_{n,n} \end{bmatrix} \times \begin{bmatrix} MAG_1 \\ \vdots \\ MAG_n \end{bmatrix} \tag{7}$$

Table II. Summary of element in the proposed agent-based model

Standard ABM elements	In proposed agent-based method	Equivalent in formulations	Type
Agent	Customer's preference for each part	$CP_{i,j}(t)$	Agent
Agent attributes	Activity; flexibility; sociability	n/a; $\varphi_{tech}(i, j, p)$; $\gamma_{frd}(i, j, t)$	Parameter
Agent to agent interaction	Customers' interaction	Equation (2)	Event
Environment attributes	Technology progress rate; technology broadcasting time	$R_{tech}(j)$; P_i	Parameter
Agent to environment interaction	Technology adoption	Equation (3)	Event
Other attributes	Product life time; number of customers; number of technologies; product components	$P_m(t_{mn})$; I; n/a; J	Parameter

The dependency matrix (INT) is evaluated using a cross-functional group of experts and product designers. Obviously, the diagonal elements on INT are valued as zero. Finally, vector CHG is used for the product revision and redesign decisions.

3.2 BDA approach for the prediction and transferring changes into PD

The use of BDA for PD, operations, and logistics is increasing (Dutta and Bose, 2015). A review of recent progress in analyzing uncertain and probabilistic data for BDA showed that these methods are mostly based on traditional databases and data sets which provide some errors in the model (Pei, 2013). Hence, we proposed a new method to quantify changes in a product life cycle using BDA. The method is extended based on huge data sets publicly available to investigate changes in PD process (Afshari and Peng, 2015). In addition, this is the first time that internal changes of parts are measured under external effects using BDA.

It is justified to develop a BDA method for this research. First of all, it is required to improve limitations of the ABM. The proposed ABM considers updates in product-related technologies as technical events while there are many other technical events that may also affect technical knowledge of customers as well. In terms of social factors, the ABM counts the media and the network of friends; however, effects of the other events are ignored. Finally, the ABM simulates agents' interactions in a limited scope of time and location. Such isolation is barely witnessed in the real product life cycle. Thus, the BDA method is proposed to overcome the limitations by using the real data. Because the data used for the analyses entails the consequences of several social, technical, and environmental factors, the analysis quality is ensured and the simulation is not required. In addition, using global sources of data provides more comprehensive results compared to the ABM method. Table III summarizes the improvements achieved using the BDA method.

The social network mining has shown great potentials as a valuable source for BDA (Song *et al.*, 2014). The study showed that if a user's opinion is stated in online space, the preferences of entire customers in the market will be affected. This study uses three years analyzed data to conclude the interconnectedness between customers' preferences. The proposed model applies potentials of the social network analysis to evaluate changes in product design.

The method has two main modules including change prediction and change transferring as shown in Figure 5. The method initiates with choosing a product and

Criteria	Agent-based modeling	Big Data analytics
Technical		
Product technology evolution	✓	✓
Global technology evolution		✓
Social		
Friends and media	✓	✓
Regulations, politics, etc.		✓
Scope of data		
All times and locations		✓
Customized scope	Limited to simulation	✓

Note: ✓ show if the defined criteria are applicable for assessed methods (agent-based modeling and Big Data analytics). Thus each ✓ represent 1

Table III. Comparison of the proposed methods in terms of technical factors, social factors, and scope of data defining scope and market. By decomposing the product into its components and subsystem, we can collect customers' data called voice of customer. Using the QFD technique, the data are transferred into FRs. Some essential decisions such as customer zone, sample size of survey, and members of the expert team are made in this step. The output of QFD survey is a list of FRs which is used for the keyword search and data aggregation in next step.

Lack of access to required data are a common challenge affecting most of the Big Data analyses. Despite the efforts in developing several tools, the complexity of proposed tools and scarcity of reliable data limit Big Data analyses. Google Trends and Google Correlate are two online products for researchers based on Google search. Google Trends indicates how often a particular search-term or keyword is searched either in total or in detail (languages and regions in the world) since 2004. Google Correlate searches across millions of candidate query time series to find the best matches for selected time series. Google Correlate finds web searched terms according to user-provided time series of data. Google Correlate algorithm uses efficient techniques such as Asymmetric Hashing which enables it with fast searches, high-recall results, and supported holdouts (Vanderkam *et al.*, 2013). Hence, Google Correlate provides optimal predictions for researchers in efficient time. Both tools have been used as popular search tools in different fields. For example, in healthcare, Google Trends was used to track Influenza-like-illnesses in a population (Ginsberg *et al.*, 2009). Also in business, Preis *et al.* (2010) presented that there is a correlation between Google Trends data searched for a company and transactions volume of its stocks in market on a weekly time period. The efficiency of proposed examples in addition to the simplicity and applicability of Google tools inspired us to use them as a valuable source for BDA as shown in Figure 6.

An effective data collection using Google Trends requires accurate keywords, specifically for keywords consisting of more than one word. To generate proper keywords for search, a list of FRs prepared by the QFD survey is utilized. There are multiple cases that keywords should be revised to start over the search. A researcher should check if the collected data are properly distributed on the world map (or defined scope of study). In some cases, the data are limited to one or some countries; therefore, revising keywords are essential. Google Trends lists a set of similar keywords matched with used keyword. If the similar keywords are not consistent with chosen keyword, revising keyword is inevitable.

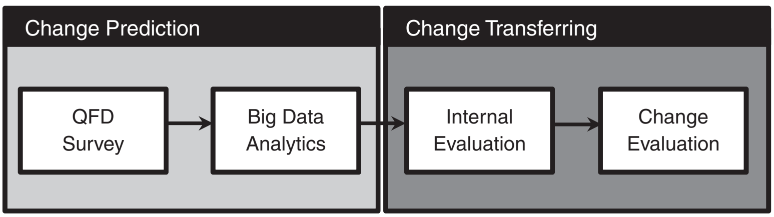


Figure 5.
Proposed method to quantify changes of product using big data analytics (BDA)

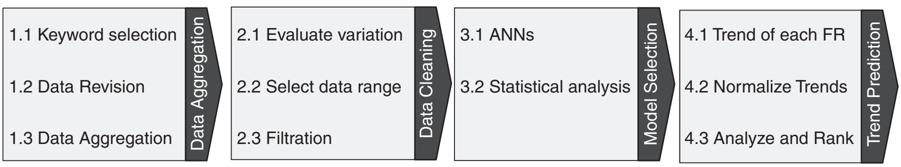


Figure 6.
Detail transactions in big data analytics

In Data cleaning, also called data cleansing or scrubbing, inconsistencies and errors within the data are removed. The aim is to improve the quality of data prepared for trend predictions. There are several methods and tools to clean the data. For a product life cycle, a major concern in data cleaning is unusual fluctuations in the searched trends. To remove such sudden changes, the reasons should be investigated and unacceptable results should be removed. In our case, the search trends about product features abruptly change when a new product is about to release. Moreover, the collected data for all keywords should contain a similar time period (e.g. last three years).

A proper model is then selected to estimate the trends in data sets. Several tools and methods are available to choose (Petropoulos *et al.*, 2013). We found two methods widely used in the literature for predicting the trends. Artificial Neural Networks (ANNs) are defined as systems of interconnected "neurons" to compute values based on input data. ANN is used for pattern recognition and machine learning because of its adaptive nature. Statistical analysis methods measure statistics of a data set. Several software packages are available to estimate trends within a data set.

Finally, the trends for FRs are estimated and normalized. Normalization helps comparing the trends in a unique unit. The normalized trends are evaluated to highlight the most affected FRs. The output of BDA is a vector of quantified values of changes transferred into components of a product.

Both the ABM method and Big Data analytic method use the "change transferring" module as shown in Figure 5. The advantage is providing a common basis to compare results. In next section, a product is studied and methods are compared.

4. Case study

Proposed methods are used to quantify changes of a product during its life cycle. We model the changes of a smartphone as uses of smartphones are increasing. In addition, a smartphone consists of multiple components and parts with interdependencies of some parts, which make it a good example for both methods (see Figure 7). There are mutual steps in the proposed model described together including: QFD survey, internal evaluation (see Table IV), and change evaluation (see Table VI). Moreover, the proposed methods are compared with the method based on DFV (Nadadur *et al.*, 2012).

Figure 7.
Exploded view of the smartphone to model changes in its life cycle

Table IV.
Evaluation of interdependencies between components of studied smartphone

To From		A	B	C	D	E	F	G	H	I	J	K	L	M	N	Sender
Display	A	0	6	0	3	0	0	0	0	1	3	0	0	6	0	19
Touchscreen	B	6	0	0	1	0	0	0	0	1	1	0	0	3	0	12
Sound	C	0	0	0	1	0	0	0	0	1	1	0	0	0	1	4
Processor	D	3	3	1	0	1	1	6	3	6	3	1	6	0	0	34
DRAM memory	E	1	1	1	0	0	3	0	0	1	0	0	1	0	0	8
Flash memory	F	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
Data transfer	G	0	0	0	3	0	0	0	9	3	1	1	0	0	3	20
Internet-connectivity	H	0	0	0	1	1	0	6	0	1	3	1	0	0	0	13
Software	I	1	0	1	3	0	0	0	0	0	1	0	0	0	1	7
Battery	J	1	1	1	1	0	0	0	0	1	0	0	1	1	3	10
GPS	K	0	0	0	1	0	0	0	0	1	0	0	0	0	0	2
Cameras	L	0	0	0	1	0	0	0	0	1	3	0	0	1	0	6
Outer facing	M	6	1	0	0	0	0	0	0	0	0	0	0	0	0	7
Physical interfaces	N	0	0	0	0	0	0	0	0	1	6	0	0	1	0	8
Receiver		18	12	4	15	3	4	12	12	18	22	3	8	12	8	

To keep a consistency between measurements, similar data and QFD matrices are used in the proposed methods as presented in Appendix.

The QFD technique uses two transforming matrices. For the survey, customer's preferences, features, and expectations from a smartphone were collected. An expert team was employed to transfer customers' preferences into FRs. FRs were then mapped into individual parts and components.

4.1 Application of ABM for the smartphone

The current and future technologies for each part are searched using a list of components. One approach is to consult with manufacturers and follow their strategic plans to ensure the accuracy of estimations. The value of parameters related to events and interactions, presented in Table II, are obtained using associate rule mining and classification algorithms (Lee *et al.*, 2015). These algorithms are known as efficient techniques to extract unknown parameters in databases. After preparing the list of values for defined parameters, the software package is used to simulate the product life cycle.

AnyLogic 6.8 is used to simulate the proposed model. Following discussion is based on the AnyLogic, but the presented logic is applicable for other software packages.

Initial setup is defining agents and the type of network. Customers are defined as agents and a list of preferences is assigned to each agent. Agents' interactions with other agents and with the environments are modeled using state charts as presented in Figure 8.

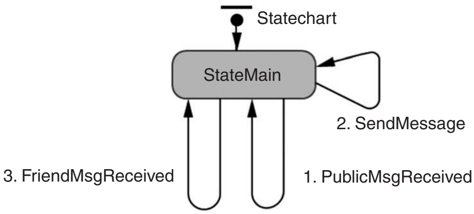


Figure 8.
Defined state chart for agents' interactions

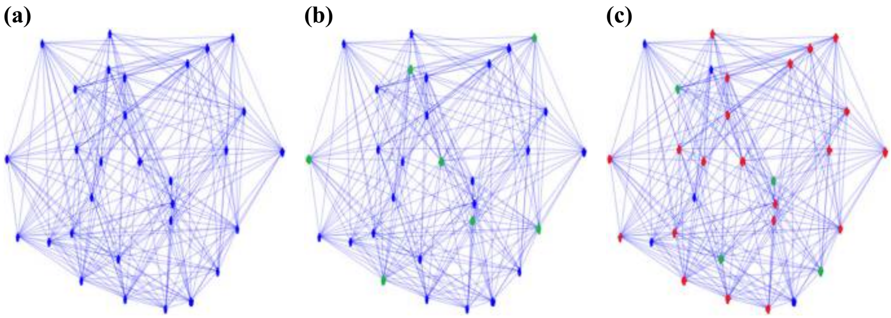
Customers divided into two groups. Technology followers update their preferences when interacting with public media (e.g. advertisement, technical reports, social networks, etc.). This event is shown as "publicMsgReceived" in Figure 8. After updating the preferences based on advertised technology, the second interaction commences called "sendMessage." In this interaction, agents broadcast their preference to other connected friends. As agents are autonomous, they may accept other agents' invitation to update the preferences. This is organized by defining a flexibility rate for each agent. If the flexibility rate of a receiving agent is higher than a sender agent, preferences of the receiving agent are updated, shown as "friendMsgReceived." Otherwise, agents will not update their preferences.

In the Anylogic package, the type of a network defines how the agents are connected together. If "Ring Lattice" is selected, agents will interact to local agents. "Random Network" denotes global connections. "Small World" is the combination of both described networks. The type of a network is selected as "Small World" to resemble real world conditions.

AnyLogic provides a step wised graphical representation for simulation, illustrated in Figure 9. In the figure, friends are connected together using lines. After initializing the simulation, all agents are set in blue color. Following interactions in Figure 8, the public message by media is sent to all agents. Technology follower agents who updated their preferences will show up in green color. Specific time periods are set for broadcasting technologies and interactions with friends. If an agent accepts a friend's invitation, its preferences are updated and its color tends to red. The simulation continues up to a particular time (three years) to resemble the product life cycle.

At the end, an average of preferences is measured as presented in Equations (4) and (5). The output is quantified values of changes transferred into individual components of the smartphone. To finalize the quantified values of changes, the effects of internal changes should be evaluated. The expert team is again employed to evaluate the relationship between parts as formulated in matrix INT of Equation (7). Table IV summarizes the analysis of dependencies between components of the smartphone. Dependency values are not symmetric to diagonal; therefore, it matters if a component is sending or receiving a change.

Dependencies are rated between 9 (if small changes in the specifications impact the receiving component) to 0 (no specifications affecting component). Summation of assigned rates shows that changes in some components have significant impacts on



Notes: (a) Start-up of simulation, all agents are in blue color; (b) technology broadcasting, technology follower agents turn to green; (c) agent accepting a friend's invitation turn to red

Figure 9. Graphical representation of simulation steps

others (e.g. processor), and some components are vulnerable to changes of other components (e.g. battery). Using Equation (7), the mutual effects of external and internal changes are evaluated for each component. Final result is discussed in Analysis and Discussion section.

4.2 Application of BDA for the smartphone

Figure 10 shows that despite decreasing trends for searching "cell phone" and "mobile phone" terms, the interest for "smartphone" is increasing, particularly since 2010. This is a simple example to demonstrate how Google Trends works for our research. Because it is proved that there is a correlation between Google search and success of a product in the market, we targeted to evaluate the changes in customers' preferences, FRs, and product components using proposed method. Moreover, to increase the clarity of the proposed methods, a sequence of analysis, outputs, and referred figures and tables are presented in Figure 11.

To keep the consistency of results and being able to compare both proposed methods, we use the same results from the QFD survey in the proposed agent-based method. The output of first QFD matrix is a list of FRs which is used to choose keywords. These keywords were then used to extract data sets by Google Trends. Following transactions proposed in Figure 6, it was noticed that in several cases the selected keywords could not represent the corresponding data set (e.g. limited to specific locations or countries, abrupt jumps, unknown distributions, etc.). Hence, the keywords were revised to collect proper data sets. If several data sets were collected for a unique keyword, data sets should be aggregated. Google Trends concludes each keyword search with a simple downloadable format; therefore, the data sets for each FR did not require aggregation. For the smartphone, we searched all keywords across the world in English language since 2004. The collected data are refined using a data analytics method described in following paragraphs.

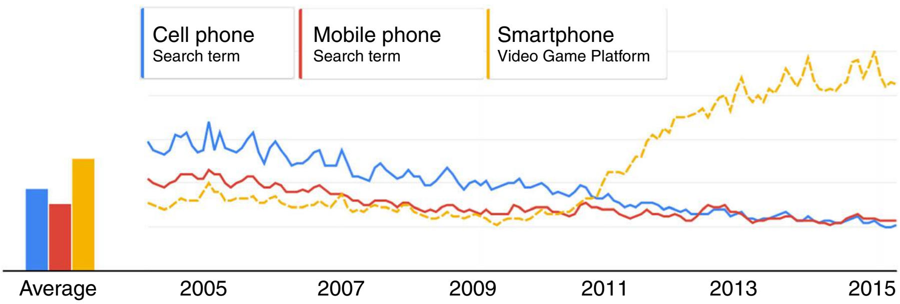


Figure 10.
Interest over time for selected key work search "Cell Phone," Mobile Phone," and "Smartphone" using Google Trends

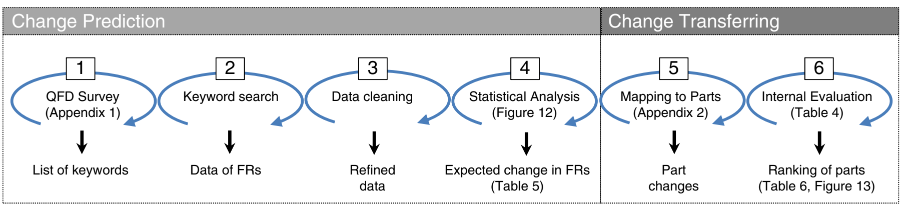


Figure 11.
Sequence of analysis for the proposed Big Data analytics methods

Data cleaning is essential for using Google Trends. We monitor variations within each data set (stemming from seasonal effects or any unpredictable events). If a point of data is recognized as a noise, the point is deleted to maintain validity of trend. It is noticed that the trend for some FRs has been shifted or changed several times since 2004. Because of such a long period, multiple events could contribute to the changes. For example, some events in macro economy (e.g. recession) had affected customers' behavior in specific years. Filtering the data to specific periods could remove the reviewed effects.

After data cleaning, we use a statistical analysis method to measure the trend for each FR. Different regression types were tested to identify the best fit with least error. Linear regression is the best correlation coefficient among regression types to measure the trends of FRs. In Figure 12, two examples of the regression analysis for FRs are presented. The slope of a trend line represents the amount of changes in interest over time for each FR.

Considering the linear regression equation ($y = ax+b$), the values of slope (a) and intercept (b) are listed in Table V. Also, the measured values of slopes are normalized to compare changes of interest over time for 25 FRs. After mapping FRs into related components of the smartphone (Figure A2), we could measure the external changes (caused by changes in customers' preferences) transferred into the components.

To evaluate the internal dependencies between the components of the smartphone, the same matrix INT in the agent-based method is utilized. Detail results for transferring changes into components considering interdependencies are presented in next section.

5. Analysis and discussion

In both proposed methods, the second module (transferring changes) is common. Using Equation (7) and interdependency analysis in Table VI, the total changes transferred into components of the smartphone are measured. Quantified values of changes are presented in Table VI. To compare efficiency of the proposed methods, the changes (CHG_{real}) in the components of the smartphone since it was introduced to the market are presented.

The magnitudes of changes are normalized to compare the efficiency of proposed methods. Error measurement indexes are used to compare normalized magnitudes of the changes with the real changes. The best method should present the least measurement error to real changes of the smartphone. Summary of error measurements for the methods is shown in Table VII. In parallel, we compared the proposed methods in this paper with the DFV method applied by Nadadur *et al.* (2012); therefore, GVI index is measured for the smartphone.

It is notices in Table VII that the proposed methods have shown the least error. Comparing error indexes for the real magnitude of changes determines that the second proposed method (BDA) has the most convergence to the real changes of the smartphone. It can be concluded that evaluating the changes using BDA is the best method when both external and internal effects are measured. Ranks in real number of changes propose that the agent-based method provides the minimum error. This is the proof of the efficiency for proposed methods.

Evaluating the internal dependencies between parts (INT) in both methods has provided a higher convergence to the real changes of the smartphone. In Equation (7), the vector of MAG is multiplied to the matrix of INT to ensure that dependencies between parts are considered in modeling and quantification of changes. Results in

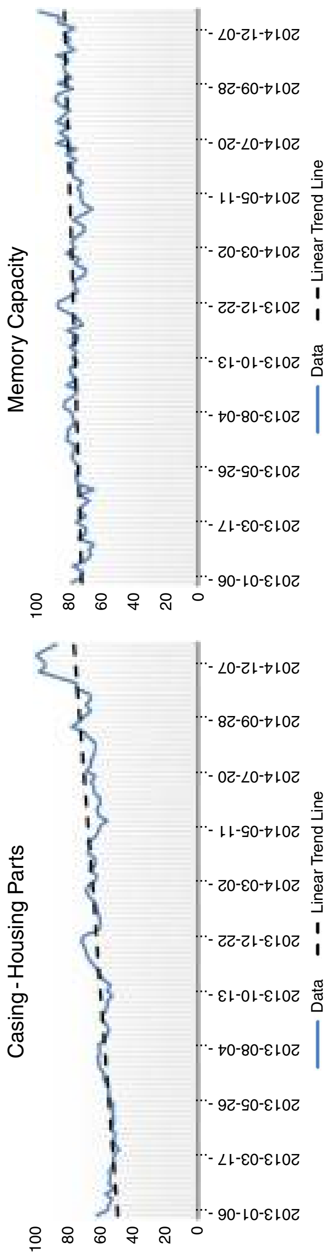


Figure 12.
Measured trends for FRs using a linear regression model

No.	FRs	a	b	Norm a
1	Display size	0.102	40.49	4.18
2	Display Resolution	0.038	62.17	1.57
3	Touch-size	0.075	70.76	3.10
4	Touch-tech	0.152	64.45	6.26
5	Audio codec	0.027	49.94	1.10
6	Mic sensitivity	0.070	60.08	2.89
7	Speaker loudness	0.056	25.35	2.32
8	Processing speed	0.155	51.81	6.37
9	Memory capacity	0.105	71.19	4.32
10	Operating system	0.107	42.96	4.41
11	Apps	0.107	67.99	4.42
12	GSM and CDMA	0.034	29.35	1.42
13	Frequencies	0.034	29.35	1.42
14	Baseband processor	0.077	19.55	3.18
15	Baseband support	0.094	41.54	3.87
16	Download speed	0.085	57.00	3.51
17	WiFi speed standards	0.208	42.38	8.56
18	Bluetooth	0.083	35.56	3.40
19	Capacity – power	0.180	55.49	7.43
20	Connector cable	0.204	51.82	8.39
21	GPS	0.067	43.27	2.77
22	Cameras-resolution	0.016	14.73	0.68
23	Cameras-video	0.059	21.69	2.42
24	Casing-housing parts	0.258	49.38	10.63
25	Casing-interactive parts	0.034	15.04	1.39

Table V. Measurement of changes transferred into each FR using linear regression equations

			CHG_{ABM}		CHG_{BDA}		CHG_{real}	
	MAG_{ABM}	MAG_{BDA}	Value	Norm	Value	Norm	Value	Norm
Display	11.93	12.65	913.1	24.08	1,346.8	36.26	2	33.33
Touchscreen	21.93	49.55	684.8	18.06	1,059.4	28.52	4	66.67
Sound	7.41	7.70	204.8	5.40	194.5	5.24	4	66.67
Processor	100.00	97.02	3,791.6	100.0	3,714.1	100.0	6	100.0
DRAM memory	19.21	15.20	293.6	7.74	254.3	6.85	3	50.00
Flash Memory	18.26	13.15	175.9	4.64	155.8	4.19	3	50.00
Data transfer	41.33	40.95	1,556.7	41.06	1,536.1	41.36	5	83.33
Internet-connectivity	21.67	22.49	953.7	25.15	952.0	25.63	3	50.00
Software	55.03	44.10	1,225.6	32.32	1,199.9	32.31	6	100.0
Battery	0.99	7.43	679.3	17.92	884.9	23.83	6	100.0
GPS	4.14	16.64	171.3	4.52	193.7	5.22	2	33.33
Cameras	10.55	18.49	683.5	18.03	715.7	19.27	4	66.67
Outer facing	29.93	75.23	376.9	9.94	813.1	21.89	4	66.67
Physical interfaces	18.54	36.06	337.7	8.91	485.4	13.07	2	33.33

Table VI. Evaluated magnitude of changes for each FR using proposed methods and real changes of the smartphone

Table VII shows that such consideration for change transferring is effective. Reviewing the error indexes per MAG_{ABM} and MAG_{BDA} columns, the error indexes are reduced when compared to CHG_{ABM} and CHG_{BDA}. Although the efficiency of the proposed method is presented, we believe that the current method to apply internal dependencies can be further improved in future work.

For the proposed agent-based method, a sensitivity analysis was conducted. The main purpose is to assess effects of different values of parameters in the agent-based simulation. If the method can provide stable results under different scenarios, it is concluded that the results of the method is reliable in the selected environment. Otherwise, sensitive parameters are highlighted for the designers to monitor. Some scenarios are defined and the rank of changes is measured as shown in Table VIII. The ranks are stable in five scenarios. Some minor changes are witnessed for the scenarios 6-8. Therefore, the shorter product life cycle, weight of imitation, and weight of innovation are assessed as important parameters. Obviously, the sensitivity analysis is not necessary for the BDA as the parameters are obtained from real data sets.

Finally, the quantified changes of parts in the smartphone life cycle are ranked. The proposed methods have shown a good prediction of changes in the product life cycle, as the graphical presentation illustrates in Figure 13.

Both methods reported very similar rankings of the parts. Top five parts are processor, data transfer, display, software, and touchscreen. Therefore, designers can make proper strategies to deal with changes in the smartphone components in the design stage. A list of strategies to manage changes in the product life cycle is presented by Martin and Ishii (2002). It is believed that an accurate knowledge on quantified changes of product components in the design stage can help designers in revising product to maximize customers' satisfaction. Consequently, such approaches improve manufacturers' profitability and market share by continuously satisfying its customers.

Table VII. Error measurement for the proposed methods

Source data	Error index	MAG_{ABM}	MAG_{BDA}	CHG_{ABM}	CHG_{BDA}	GVI
Real magnitude of changes	Least absolute deviation	186.5	226.0	194.7	169.0	295.0
	Least deviation	−152.5	−9.3	−162.2	−116.4	137.0
	Mean percentage error	−31.33	19.06	−34.22	−21.28	58.04
	Mean squared error	6.71	4.76	2.59	1.78	5.03
Rank in real number of changes	Least absolute deviation	44.0	48.0	41.0	43.0	46.0
	Least deviation	0.0	0.0	0.0	0.0	−25.0
	Mean percentage error	33.98	40.19	19.73	20.22	6.18
	Mean Squared error	3.21	3.22	1.64	1.40	2.16

Table VIII. Sensitivity analysis for the selected parameters in the proposed agent-based method

		Ranking of the changes in the smartphone parts													
Scenarios	Direction	A	B	C	D	E	F	G	H	I	J	K	L	M	N
Number of customers	↑	11	8	12	1	5	6	3	7	2	14	13	10	4	9
Number of friends	↑	11	8	12	1	5	6	3	7	2	14	13	10	4	9
Number of far friends	↑	11	8	12	1	5	6	3	7	2	14	13	10	4	9
Rate of tech. evolution	↑	11	8	12	1	5	6	3	7	2	14	13	10	4	9
Product life cycle	↑	11	8	12	1	5	6	3	7	2	14	13	10	4	9
Product life cycle	↓	10	5	12	1	7	9	3	6	2	14	13	11	4	8
Weight of imitation	↑↓	10	5	12	1	7	9	3	6	2	14	13	11	4	8
Weight of innovation	↑↓	10	5	12	1	7	9	3	6	2	14	13	11	4	8

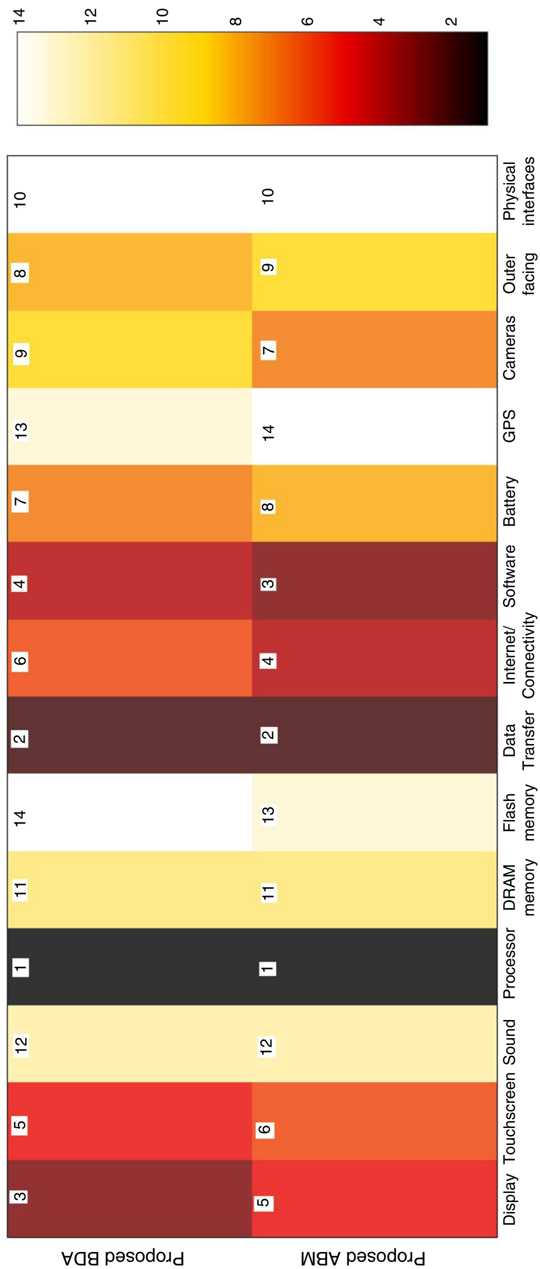


Figure 13.
Ranking of the components using the proposed agent-based method and Big Data analytics method

6. Conclusions

This paper presents two methods to model and quantify uncertainty during the PD process. Two different sources of uncertainty are evaluated. Changes of customers' preferences are considered as external uncertainty, and interdependencies between components of a product are referred as internal uncertainty. In a knowledge economy, a significant part of a company's value may consist of intangible assets. It is believed that the knowledge economy depends on more intellectual capacities than physical inputs as a key aspect (Powell and Snellman, 2004). For an efficient use of intellectual properties in the PD process, this research developed a cost-effective method to estimate changes in product components using the Big Data during their life cycle. The early knowledge of the product changes will minimize the cost and increase the efficiency of design decisions. Summary of research findings is presented as follows:

- Two methods are proposed to bridge the reviewed gaps in the literature. The first method focusses on the ability of ABMs in the multiple domain analysis of changes. Technical and social interactions are defined for a set of autonomous agents. Agents' behavior for a specific duration (the product life cycle) is simulated. The proposed agent-based method can help formulating the mathematical representation of interactions.
- A competence method based on BDA is developed to overcome shortcomings of the proposed ABM in terms of technical factors, social factors, and scope of study. BDA has shown a great potential for decision making in different fields. The method quantifies the changes in customers' preferences using social network mining. After quantifying the external uncertainty, effects of the dependencies between components of a product are evaluated. The changes are then transferred into components to determine the most affected components during the product life cycle.
- Both methods are validated using the smartphone product. The methods are presented with details to support the implementation for any product. For the agent-based method, a commercial software package is used; however, the proposed framework can be implemented using any other software packages.
- Results of the proposed method for the smartphone are discussed in detail. Real changes of the smartphone during its life cycle are used to assess the accuracy and efficiency of the proposed methods. Some error indexes are used to quantify the error measurement as shown in Table VII. Moreover, a change propagation method (GVI) applied for the smartphone (Nadadur *et al.*, 2012) is used to compare the results. Both of the proposed methods have shown interesting results, but the method based on BDA has shown a better convergence to real changes of the smartphone. It is noticed that evaluating the dependencies between the components of the smartphone could increase the accuracy of the methods.

Limitation in this study includes a lack of access to other sources of Big Data to compare with the used sources. Therefore, we trusted several studies that confirm Google Trends as a valuable source for the BDA. For the future research, the authors plan to evaluate effects of the quantified uncertainty on different design objectives (e.g. product cost, development time, environmental impacts of a product, etc.). In addition, it will be useful to evaluate and optimize design parameters under uncertainty when multiple design objectives are demanded. It is believed that such studies will help designers making the optimized solution in the product design stage.

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(The Appendix follows overleaf.)

Appendix

Functional Requirements / Customer Requirements	Display		Touchscreen		Sound			Processing and Memory		OS	Apps	Data Download and transfer					Internet and Connectivit		Power Capacit	Connector cable	GPS	Cameras		Casing	
	Size	Resolution	Size	Technology	Audio codec	Mic sensitivity	Speaker loudness	Speed	Capacity			GSM andCDMA	Frequencies	Baseband processor	Baseband memory support	Download transfer speed	WiFi speed Standards	Bluetooth				Resolution	Video	Housing parts	Interactive parts
Display																									
Large size display	✓																							✓	
High-res disp		✓																							
Easy touchscreen operation			✓	✓																					
Scratch-resistant screen				✓																					
Sound																									
Sound-Good quality					✓	✓	✓																		
Sound-Support different music file										✓	✓														
Sound-Fast processing								✓		✓	✓				✓	✓	✓	✓							
Sound-Large storage capacity									✓																
Data transfer/Download																									
Fast												✓	✓	✓	✓	✓	✓	✓		✓					
Easy to sync										✓								✓		✓					
Connectivity																									
Multiple carriers												✓	✓												
Good coverage												✓	✓												
Internet																									
Easy WiFi connectivity																	✓								
Easy web browsing											✓				✓	✓	✓								
Easy emailing facility											✓														
Easy video viewing	✓	✓									✓					✓	✓								
OS and applications																									
Cool and versatile OS								✓		✓	✓														
Wide selection of apps									✓	✓	✓														
Easy app download and install								✓	✓	✓	✓					✓	✓			✓					
Easy to customize and update										✓						✓	✓			✓					
Multitasking capability								✓		✓	✓														
Power management																									
Simple charging																				✓					✓
Short charging time																			✓						
Long b/w charge intervals																			✓						
Reliable																									
Robust and sturdy																								✓	✓
No software glitches										✓	✓														
Others																									
Easy to activate silent mode																									✓
Customizable ringtone										✓															
Easy typing	✓	✓	✓	✓						✓														✓	
Voice activation					✓	✓	✓			✓	✓														✓
Global positioning (GPS)										✓	✓					✓	✓				✓				
Good front and back camera																						✓	✓		✓
Overall sexiness (aesthetic)	✓	✓																		✓				✓	✓

Figure A1.
First QFD matrix for the smartphone

Customer Requirements \ Smartphone components	Display	Touchscreen	Sound	Processor	DRAM memory	Flash Memory	Data transfer	Internet and connectivity	Software	Battery	GPS	Cameras	Outer facing	Physical Interfaces
Display														
Size	4.18	4.18											4.18	
Resolution	4.71	4.71												
Touchscreen														
Size	3.10	3.10											3.10	
Technology		37.56												
Sound														
Audio codec			1.10											
Mic sensitivity			2.89											
Speaker loudness			2.32											
Processing and memory														
Speed				57.33	6.37									
Capacity						4.32								
OS				26.46	4.41	4.41			13.23					
Apps				13.26	4.42	4.42			13.26					
Data Download and transfer														
GSM and CDMA							12.78							
Frequencies							4.26							
Baseband processor							9.54							
Baseband memory support							3.87							
Download transfer speed							10.53	10.53						
Internet and connectivity														
WiFi speed Standards								8.56						
Bluetooth								3.40						
Power capacity										7.43				
Connector cable														
GPS									8.31		16.62			
Cameras														
Resolution	0.68								2.04			4.08		
Video									7.26			2.42		
Casing														
Housing parts												10.63	63.78	31.89
Interactive parts			1.39									1.39	4.17	4.17
Magnitude of Changes	12.65	49.55	7.70	97.02	15.20	13.15	40.95	22.49	44.10	7.43	16.64	18.49	75.23	36.06

Figure A2. Calculation of magnitude of changes for the smartphone

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